1. Introduction

The globalization of markets has put global brands (GBs) on the center stage. The evidence is everywhere: on the streets, in stores, in homes, in the media. Global brands are exerting their power and influence within various economic, cultural, and psychological domains. In line with this increased importance, many multinational corporations are allocating more attention and resources to fewer brands with global potential. As the economic clout of global brands increases, decisions about their development, measurement and strategic management become of paramount importance, raising new questions. How can global brands be created, managed, and marketed most efficiently and successfully? Are existing constructs, theories and methodologies capable of capturing the new realities of global brands or do we need to develop new frameworks and theories for academic and practitioner use?

Our interest in global brands led to a conference in Istanbul on global branding organized at Koç University, Istanbul in June 2010. The objective was to advance knowledge about global brand management (GBM) by disseminating new research and by encouraging the evolution of new research themes. To this end, top level practitioners from leading multinational companies with global brand development and management responsibilities shared their experiences and concerns and also were exposed to some of the recent academic thinking. In the conference, based on evaluations by a panel of experts we accepted thirty submissions for presentation. After the conference, we published the call for papers for the IJRM Special Issue and encouraged further submissions. We received 28 papers and we used the high standard process in place at IJRM for evaluating regular submissions. We acted as Associate Editors and worked together with Marnik Dekimpe throughout the review process. All submissions underwent IJRM’s standard double-blind review process. The result is this special section with 5 papers with an acceptance rate of 18%. We believe these papers provide interesting, valid and new results and extend our knowledge.

This section introduces the five articles that appear in this special section on global brand management. The main objective is to provide a roadmap that places these articles in the context of the GBM landscape.

2. What is known about GBM

Before assessing what is known about GBM, we begin by painting the background that put global brands in the center stage. Developments accelerating the trend toward global market integration include the emergence of global media, the Internet, and mobile communications, the free movement of capital and goods leading to worldwide investment and production strategies, rapid upgrading and standardization of manufacturing techniques not only in the developed world but also in emerging economies, growing urbanization, rapid increase in education and literacy levels, and expansion of world travel and migration (Ritzer, 2007; Yip, 1995). These forces make global brands appealing from both the demand and supply side perspectives. From a supply side perspective, global brands can create economies of scale and scope in research and development, manufacturing, sourcing, and marketing; They provide an ability to exploit good products, ideas, and executions in multiple markets (Maljers, 1992; Özsomer & Prussia, 2000; Yip, 1995); From the demand side, global brands, with their worldwide availability, awareness and consistent positioning may benefit from a unique perceived image or “myth” worldwide (e.g., Alden, Steenkamp, & Batra, 1999; Holt, Quelch, & Taylor, 2004). Such a global positioning increases in its strategic appeal as large consumer segments around the world develop similar needs, tastes, and aspirations (Özsomer & Simonin, 2004; Steenkamp, J.-B, & Ter Hofstede, 2002; Steenkamp, J.-B, & de Jong, 2010). Thus we believe that GBM represents an evolution, integration, and interaction that go beyond the level captured by existing brand management approaches leading us to the following proposition.

P1: GBM is the outcome of the continuing evolution, integration, and interaction of world markets necessitating new conceptualizations, theories, and methods to its study.

A prerequisite for an emerging field to coalesce into a more established field is for the discipline to establish an acceptable definition that captures all the major aspects of the concept (Parvatiyar & Sheth, 2001). The abundance of definitions of GBs has caused some confusion. Özsomer and Altaras (2008) document numerous definitions of global brands in the literature and categorize them as capturing either a supply or demand focus. For example, studies on
standardization have defined global brands as those that use similar brand names, positioning strategies, and marketing mixes in most of their target markets. Some brands are more global than others with respect to differing levels of achieved standardization (Aaker & Joachimsthaler, 1999; Johansson & Ronkainen, 2005; Kapferer, 2005). Thus, in this research stream, the definition of a global brand is based on the extent to which brands employ standardized marketing strategies and programs across markets.

The second stream, focusing on consumer perceptions (Alden, Steenkamp, & Batra, 2006; Batra, Ramaswamy, Alden, Steenkamp, & Ramachander, 2000; Dimoffe, Johansson, & Iikka, 2008; Hsieh, 2002; Steenkamp et al., 2002; Steenkamp, J.-B., Batra, & Alden, 2003; Strizhakova, Coulter, & Price, 2008; Zhang & Khare, 2009) defines global brands as the extent to which the brand is perceived by potential and existing customers as global and as marketed not only locally but also in some foreign markets. This definition implies that as the perceived multimarket reach and recognition of a brand increases, the perceived brand globalness increases as well (Steenkamp et al., 2003). Both demand and supply based approaches complement each other and have made significant contributions to the GB literature. We believe a working definition of GBs should incorporate both perspectives, although different studies may focus only on one dimension. This leads to our second proposition:

P2: The field of GBM has begun to converge on a common definition.

Incorporating the many definitions presented in the studies cited above, we suggest the following definition: Global brands are those that have global awareness, availability, acceptance, and desirability and are often found under the same name with consistent positioning, image, personality, look, and feel in major markets enabled by standardized and centrally coordinated marketing strategies and programs.

3. Global brand strategy development and implementation

Having provided a working definition of global brands, a related issue is to understand the process of developing and managing these brands within the firm. Consistent with current trends in globalization, many multinational companies (MNCs) have shifted their orientation from the traditional multidomestic approach, in which local subsidiaries market locally developed products to the local population in a highly autonomous manner, to a global approach, in which firms market their products on a global basis with only limited adaptation to local markets (Kotabe & Helsen, 2010). An important question involves how this strategic shift takes place and how a global brand approach is implemented. Matanda and Ewing (2012), in the special section, take a firm perspective and provide a grounded theory where they document the process of global brand strategy development and regional implementation in a major MNC. Using a distinctly inductive approach and an extended case method, they find that the move to a global brand strategy focuses on ensuring accountability and capacity-building both at the regional and global levels. The process transforms the organization by increasing marketing capability locally while instilling better processes and disciplines centrally. The paper documents how global brand strategy cohesiveness is maintained in an unconventional decentralized structure. The dynamic ability to balance the autonomy regional managers so cherish with the need for consistent, over-arching global brand planning templates, structures and processes is crucial for success. Transformational leadership and high degrees of regional ‘buy-in’ are critical in facilitating strategy implementation and enable the regions to increase their marketing capabilities while leveraging off the global scale of the MNC when necessary. The paper identifies a process that has deliberately not involved a major organizational restructuring, but instead in the words of a top global manager “…its less about boxes and reporting lines. We’re changing the nervous system and the social system, not the skeleton”. Even though we consider Matanda and Ewing (2010) article conceptual rather than empirical, we note its relevance to the GBM-performance link. In particular, the conceptual framework grounded in interviews with senior global and regional marketing managers can be used as a best practice template.

4. How do consumers perceive GBs?

Both practitioners and academics are interested in understanding how consumers perceive global brands. The perceived globalness of a brand has been found to be positively related to perceptions of quality (Holt et al., 2004), prestige (Steenkamp et al., 2003), esteem (Johansson & Ronkainen, 2005), and in emerging markets to status (Batra et al., 2000). When American consumers think of a global brand, they think of worldwide presence and recognition, standardization or lack of local adaptation (Dimoffe et al., 2008). Consumers also associate a higher ethical burden with global brands relative to local ones, and expect global brands to behave in a socially responsible manner in the markets they serve (Dimoffe et al., 2008; Holt et al., 2004). This leads to our next proposition:

P3: Consumers expect global brands to behave in a socially responsible manner in the markets they serve.

Torres, Bijmolt, Tribó, and Verhoef (2012) empirically demonstrate that corporate social responsibility (CSR) to various stakeholders (customers, shareholders, employees, suppliers, and community) has a positive effect on global brand equity (BE). Using panel data comprised of 57 global brands they show that CSR to each of the stakeholder groups has a positive impact on global BE. Furthermore, in their study, global brands that follow local social responsibility policies over communities obtain strong positive benefits in terms of the generation of BE, as it enhances the positive effects of CSR to other stakeholders, particularly to customers. In line with previous research (e.g., Dimoffe et al., 2008, Holt et al., 2004), for global brand managers, combining global strategies with the satisfaction of the interests of local communities is particularly productive for generating brand value.

5. How are consumer perceptions of GBs shaped?

Recent research has identified several antecedents of consumer's perceptions and evaluations of GBs. The extent to which consumers are pro or antiglobalization colors their global brand associations as well. Proglobals perceive global brands to have a unique global image or global myth, as such find them to be more aspirational, with high universal relevance regardless of location or culture, and less risky (Dimoffe et al., 2008, Holt et al., 2004). Even cognitively antiglobal consumers have a positive affective predisposition toward global brands, although they do not acknowledge it or may not even be aware of it in their direct responses. “Everyone feels good about global brands and what they convey to their users (Dimoffe et al., 2008).” Thus, there seems to be a component of global brand equity that is not captured by the specific brand associations (Dimoffe et al., 2008; Holt et al., 2004; Hsieh, 2002). This higher order, implicit, affective component is difficult to articulate and understand for consumers and makes the study of global brands interesting and challenging both conceptually and empirically.

Riefer (2012), in the special section, focuses on the role of globalization attitude (GA) and global consumption orientation (GCO) (Alden et al., 2006) on evaluations, attitudes, and purchase intentions of global brands. An interesting twist is the differentiation of global brands based on their domestic or nondomestic brand origin. In two empirical studies, Riefer shows that GA influences brand evaluations for three out of four tested brands, suggesting a halo-effect. Those who disfavor economic integration evaluate global brands less positively, irrespective of their domestic or foreign origin. This discount
is particularly relevant for high-involvement products. Regarding GCO, Riefler (2012) finds consumers with strong GCO using brand globalness as a quality signal and having more positive brand attitudes for domestic, but not foreign, global brands. Globally oriented consumers can more easily identify with globally successful companies from their home country, with companies that are “one of us” that “made it”.

P4: The foreign or local origin of the global brand moderates the effects of GA and GCO on evaluations, attitudes and purchase intentions.

Building on Arnett’s (2002) work on the psychological consequences of globalization, Zhang and Khare (2009) show that identifying consumers’ identity as global or local is key to understanding consumers’ attitudes toward global versus local products. A local identity means that consumers feel they belong to their local community and identify with local ways of life, whereas a global identity means that consumers feel they belong to the global community and identify with a global lifestyle. In this special section Tu, Khare, and Zhang (2012), shorten the previous 19 item scale into an 8-item managerially usable version for assessing consumers’ local-global identity. The authors also demonstrate the scale’s discriminant and convergent validity with related constructs, such as consumer ethnocentrism, nationalism, and global consumption orientation. Global consumer culture positioning, as suggested by Alden et al. (1999) would work better for the global identity segment than other segments in general.

Most recently, Steenkamp and de Jong (2010) show that consumers vary systematically and predictably in their attitudes toward global products (AGP) and in their attitudes toward local products (ALP) in that these attitudes are not just specific to a particular product but rather are generalized attitudes across a wide variety of product categories. Drawing on globalization studies (e.g., Holton, 2000, Ritzer, 2007) and consumer culture theory (e.g., Arnett, 2002), Steenkamp and de Jong show that different combinations of consumer attitudes toward global and local products produce the different attitudinal responses of homogenization, glocalization, localization and glalienation. The existence of the complex “glocal” identities of many modern consumers is also empirically demonstrated by Strizhakova et al. (2008).

In this special section, Strizhakova et al. (2012) build up on their prior work and assess “glocal” cultural identity of the young adult market on global–local identity beliefs (belief in global citizenship through global brands, nationalism, and consumer ethnocentrism) in the emerging markets of Russia and Brazil. Results across two studies indicate three distinct segments, two of which, the Globally-engaged and the Nationally-engaged, are consistent across countries. They find a third idiosyncratic segment in each country, the Unengaged in Russia and the Globally-engaged in Brazil. Strizhakova et al. (2012) suggest the Globally-engaged and the Glocally-engaged as the most viable segments for multinational firms are; these segments have an identity that is grounded in both global and local cultures and respond favorably to both global and local brands. Nationally-engaged consumers have a more localized identity; they are a more challenging target for firms offering only global brands. The Unengaged segment has weak global–local identity beliefs and low involvement with both global and local consumption practices. Based on these recent papers, we develop our next proposition:

P5: Attitudes and identity beliefs can be used effectively to segment customers into global, glocal, local, and alienated groups that cut across national markets.

6. Issues for further GBM research

We now turn to issues for further GBM research. We find it surprising that the global branding literature and the articles in this special section are largely taking a consumer focus and are silent regarding firm strategy and especially competitive reaction. We find this omission in the GBM literature especially surprising given that the evolution of global branding can be traced back to the basic trade-off between local responsiveness and global standardization. According to this literature firms can enhance performance and gain competitive advantage either by achieving local relevance through a focus on local markets and brands or by achieving economies of scale and scope through international standardization of global brands (e.g., Ghemawat, 2007; Özsomer & Simonin, 2004; Yip, 1995; Zou & Cavusgil, 2002). For example, the move by P&G to more marketing standardization favoring global brands in the late nineties has forced Unilever to respond in kind perhaps sooner than it would have done without the pressure from P&G. Thus, we believe GBM research should focus on two firm level and related questions: 1) How to integrate competition into the processes underlying GBM; and 2) How to identify the conditions under which GBM can yield sustainable advantage in the face of competitive reaction? Time series analysis tracking the performance effects of GBs over time, across different categories and markets (e.g., emerging versus mature markets) and integrating competitive reaction could provide fruitful insights. Some questions that can be studied in this context include, but are not limited to the following: Do GBs have different competitor reaction functions compared to local brands? How are their sales response functions different? Could GBs work as an insulation mechanism decreasing the effects of competitive reactions on the focal brands?

Most GBM studies with a firm level focus are interested in multinationals. However, it is possible to create a global brand even for a start-up in a very short time. These born globals (Knight & Cavusgil, 2004) such as Google, Facebook, Linked-in, Groupon have started small but have achieved global recognition, awareness and availability in a very short time. We believe that careful attention to GBM processes and structures in these born globals are further research possibilities.

Related to our previous point, the impact of social media on GBM is another issue for further research. Social media unites consumers around the world. Brand related ideas, attitudes, preferences and experiences are shared instantly. Social media’s contribution to GBM can be studied in the context of blogs, micro-blogs, and global brand communities.1 We believe that the papers in this section build on and advance our knowledge on GBM and global brands in fruitful ways. There are many people to thank. Without their support this special section would not be possible. We would especially like to thank IJRM editor Marnik Dekimpe for his dedication, professionalism, and support in every step of the process. Our special thanks also go to Cecilia D. Nalagon from the IJRM editorial office. Her attention to detail and dedication is highly appreciated. We would like to thank the authors for submitting their papers and the reviewers for their valuable time and expertise.2 It is our hope that these papers stimulate further conversation, discussion and writing on GBM.

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References


The process of global brand strategy development and regional implementation

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A B S T R A C T
Although standardization–adaptation has long been recognized as a dynamic negotiation, less is known about the attendant processes within organizations. Accordingly, this study “pulls back the curtain” on a new global brand management strategy at Kimberly-Clark (KC). An extended case method was employed, comprising three rounds of semi-structured interviews with senior regional and global marketing managers on six continents. Global brand strategy development at KC entails sharing information and best practices, implementing common brand planning processes, assigning responsibilities for global branding, and creating and implementing effective brand-building strategies. Indeed, KC’s approach, predicated on accountable empowerment and capacity-building, is transforming the organization by increasing marketing capability locally while instilling better processes and disciplines centrally. An examination of these seemingly orthogonal objectives allows us to see how brand strategy cohesiveness is maintained in an unconventionally decentralized structure.

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1. Introduction

The global integration of markets has spurred a convergence in consumer preferences (Townsend, Yeniyurt, & Talay, 2009), prompting organizations to search for more effective ways to serve international customers and enhance their worldwide competitive positions (Wang, Wei, & Yu, 2008). Within this context, globalization is defined as the distribution and creation of products and services of a homogenous type and quality worldwide (Rugman & Moore, 2001). The attempts of multinational corporations (MNCs) to globalize have resulted in the development and promotion of global brands (Townsend et al., 2009; Wang et al., 2008). Therefore, as competition globalizationizes, an MNCs’ success hinges on its ability to position and manage brands across the numerous countries in which it operates (Usunier & Lee, 2005).

Although most MNCs recognize the advantages of global brands and the value of developing effective brand strategies that nurture their global identities (Motameni & Manuchehr Shahrokhi, 1998), many are grappling with the challenges and complexities of competing in a global environment (Cavusgil, Yeniyurt, & Townsend, 2004). These complexities are amplified by the assumption that most MNCs are regional, not global, and that there is no single global market or single global strategy (Rugman & Moore, 2001). Thus, Townsend et al. (2009) argue that additional research using examples of the globalization of brands can provide managers and scholars with a deeper understanding of global brand management strategy. Prior literature has explored components of global branding and the ways MNCs can exploit global opportunities, but limited attention has been paid to branding within a global context (Cayla & Arnold, 2008). Furthermore, no consensus has been reached on the relationship between global standardization and centralization in global branding (Özsomer & Simonin, 2004; Quester & Conduit, 1996).

We sought to extend current knowledge of global brand management by deconstructing and learning from the strategies and processes of a well-known and successful global MNC. The study viewed the global brand-building process as a dynamic capability of MNCs, and the research therefore considered how dynamic and ongoing tensions are managed between global standardization and local adaptation, as well as the resultant decisions that shape corporate strategies and processes. Our focal MNC was Kimberly-Clark (KC), which provided an ideal and constant context by “setting the limits on the range of relationships to be expected” (Johns, 2001, p. 33). KC’s global marketing and branding strategy has recently undergone extensive changes, thereby providing a rich context within which to understand the processes, procedures, and practices involved in becoming a Global Marketing Organization. After presenting an extended case method (Burawoy, 1998; Kates, 2006), we focus on understanding the dynamics of the KC setting (Eisenhardt, 1989) in order to explore and build theory (Yin, 1994).

The manuscript is structured as follows: We review the literature, concentrating on global brands/branding/brand management and on dynamic capabilities; describe the case setting and the method; discuss the findings; advance a process theory of global brand management at KC; outline theoretical and managerial implications, acknowledge study limitations and provide directions for future research.
2. Literature review

2.1. Conceptualizing global brands

Van Gelder (2003) defines global brands as brands that are available across multiple geographies without any specific continental requirements. In contrast, Hankinson and Cowking (1996) define global brands as brands that possess consistency of brand proposition and product formulation. Aaker and Joachimsthaler (1999) provide a more detailed definition, proposing that global brands are “brands with a high degree of similarity across countries with respect to brand identity, position, advertising strategy, personality, product, packaging, and look and feel” (Aaker & Joachimsthaler, 2000, p. 306). Global brands can therefore be envisaged as tools that enable organizations to portray and manage consistent corporate and brand images across a diverse customer base.

In accordance with Appadurai’s (1990) ‘political ideoscope’ conceptualization, Askegaard (2006) contends that the ‘global ideology of branding’ is colored by local variations dependent on the market context. Hence, the true homogenization of world markets is less about media and consumer convergence and more about the “...consciousness of the necessity of special symbolic attributions to consumer goods in contemporary market-based economies” (Askegaard, 2006, p. 99). Indeed, the rise of a more globalized culture does not imply that consumers share the same tastes or values (which Levitt, 1983).

Rather, as Holt, Quelch, and Taylor (2004) argue, “People in different countries, often with different viewpoints on a range of issues, participate in a shared conversation, drawing upon shared symbols. One of the key symbols in that conversation is the global brand” (p. 70). According to ACNielsen (2001), a brand can be considered ‘truly global’ if it is sold in all 30 countries used in the sample (which represent 90% of the world’s gross domestic product), and if more than 5% of its sales come from outside of its home region. Further, Interbrand (2006) identifies six principles shared by the Best Global Brands: recognition, consistency, emotion, uniqueness, management, and adaptability. Kleenex, one of KC’s core brands, was named a billion dollar brand that could be considered truly global based on these definitions and principles (ACNielsen, 2001; BusinessWeek/Interbrand, 2009).

2.2. Global brand management

Although extant literature is replete with examples of ‘global’ brands (Jain, 1989), there is a dearth of prescriptive theory on “how brands become global” (Townsend et al., 2009, p. 540). Advocates of standardization suggest promoting the same brand image in all countries in which the company operates (Bennett & Blythe, 2002), while those who favor local adaptation suggest accommodating differences in marketing strategy and brand expression across markets (Van Gelder, 2003).

Several global brand management strategies have been proposed, but they tend to be limited to specific business contexts (Ger, 1999; Melewar & Walker, 2003). In a more generalizable sense, Van Gelder (2003) calls for brands to be ‘harmonized’ across markets to ascertain which aspects of the brand proposition should be the same across markets. These core aspects can then be standardized without upsetting (but rather, inspiring) local managers and/or consumers.

To determine the best way to manage a brand globally, firms must understand the extent to which factors relating to the brand vary across national boundaries (Van Gelder, 2003). Moreover, managers should be aware that in some instances, a single brand cannot be imposed on all markets (Keegan & Green, 2005). To achieve a balance between standardization and local adaptation, Kapferer (2005) proposes seven globalization strategies, all based on the notion that the brand is a system consisting of concept, name, and products or services. These strategies range from the “fully strict global model gradually to the full local model” (Kapferer, 2005, p. 323). Thus, MNCs must also deduce what processes and strategies can be standardized and how best to manage decision making authority within their organizations in order to find the balance necessary to manage global brands.

2.3. Centralization and decentralization

Centralization determines the extent to which decisions are made at high levels of executive authority in an organization, while decentralization delegates decision making to lower levels of authority (Zannetos, 1965). The type of decision making method that will be used is usually determined at an organizational (Edwards, Ahmad, & Moss, 2002) or marketing level (Özsomer & Prussia, 2000). Edwards et al. (2002) further explore these decision making philosophies in terms of the level of autonomy an MNC gives to its subsidiaries. However, determining how much control an organization exerts over its subsidiaries is not easy (Harris, 1992). Indeed, most global organizations embrace both philosophies (Heiden, 2007). Success in global markets may therefore require MNCs to incorporate both centralization and decentralization in their structures to enable them to act quickly locally while leveraging global best practices (Wickman, 2008).

2.4. Dynamic capabilities

Dynamic capability theory may help explain the ways in which firms build and reconfigure their brand strategy and decision making structures in response to changing environments (Teece & Pisano, 1994). Dynamic capabilities are a learned pattern of collective activity and strategic routine through which organizations can generate and modify operating routines to achieve new resource configurations (Eisenhardt & Martin, 2000).

Brands can be instrumental in assisting firms to build, attain and enhance their competitive advantage (Abimbola, 2001), while top management can help develop and implement a firm's dynamic capabilities (Rindova & Kotha, 2001). Indeed, when top management develops and implements a marketing strategy to reconfigure existing resources and capabilities in a turbulent environment, branding can be viewed as a dynamic capability. We conceptualized global brand management as the leveraging of knowledge-based intangible resources to facilitate learning, innovation, and knowledge transfer across global markets, and concluded that dynamic capability theory provides a suitable theoretical foundation for exploring and explaining the recent development and implementation of a new global brand management process at KC.

3. Research approach

3.1. Study context

KC is one of the world’s leading manufacturers of health and hygiene products, with manufacturing facilities in 36 countries and products marketed in more than 150 countries. In addition to being a large MNC in terms of geographic scope, KC is ranked 126 on the Fortune 500 list (Fortune, 2010). Moreover, ACNielsen (2001) identified Huggies and Kleenex, two of KC’s flagship brands, as billion dollar brands that ‘could be considered truly global’.

KC originally established its business in silos that divided the world into discrete regions, creating powerful regional organizations by operating under a business model focused on reinvigorating its product range. Recently, however, KC adopted a global brand management strategy aimed at increasing inter-organizational alignment and standardization. KC therefore provides a unique example of how global brands are managed in an MNC that has recently shifted from decentralized, regional brand management strategies to a global brand management strategy. The case also provides a unique opportunity to explore how, as Özsomer and Prussia (2000) note, the strategic decision to enhance brand standardization influences the firm’s organizational structure.
KC's new global brand management strategy was overseen by Chief Marketing Officer (CMO) Tony Palmer, a former managing director of Kellogg's United Kingdom business. Under Palmer's guidance, KC restructured its global marketing/branding process, a move aimed at changing KC into a ‘...legendary marketing company...delivering a unified brand and creating a Global Marketing Organization’ (Kimberly-Clark, 2007). In essence, this extended case study examined the global brand management processes instituted by Palmer, processes intended to “…help us find new ways to deliver the promise of our brands through product and service innovations, help us discover new and surprising ways to better connect with consumers with relevant and meaningful messages, and help us maximise the return on our marketing investment” (Kimberly-Clark, 2007).

3.2. Research design

The study employed the extended case method (ECM) (Burawoy, 1998; Kates, 2006) to examine global brand management. Cayla and Eckhardt (2008) note that ECM is the preferred method for researching the types of global and cultural questions explored in this study because it “engages with the contexts in which the phenomena occur” (p. 218). Moreover, single case studies are considered more effective in providing theoretical insights than are multiple cases (Dyer & Wilkins, 1991). Thus, single case studies can be used to describe real-life contexts in which interventions have occurred and explore situations in which the intervention being evaluated has no clear outcomes (Yin, 1994).

3.3. Interview protocol and sample

A semi-structured interview approach was used (see Appendix 1). Interviews ranged in duration from 45 min to 75 min. Telephone interviews were used in phase one, followed by face-to-face interviews in phase two and a combination of telephone and face-to-face interviews in phase three. With the interviewee's permission, all of the interviews were recorded to facilitate coding and the interpretation of direct quotes, as well as to increase the accuracy of the findings (Eisenhardt, 1989). An interview protocol was developed (based on a review of the literature) and used in all interviews to facilitate consistency and analysis. Due to the semi-structured nature of the interviews, the research protocol acted as a mechanism for guiding conversation. Open-ended questions and probing techniques were used to facilitate dialogue and discussion; the interviews began with open-ended questions to encourage the interviewees to reveal their attitudes about the research topic without limiting their responses (Dick, 1990). In total, we interviewed fifteen respondents (see Table 1 for respondent profiles). Of these, nine had global roles and six had regional roles (although this dichotomy is not as clear-cut in practice). Of the regional respondents, one was from Asia, one from Australia, one from Europe, one from sub-Saharan Africa (with responsibility extending to the Middle East) and two from South America.

3.4. Data analysis

The first stage in ECM (Burawoy, 1998; Kates, 2006) involves the reduction of empirical data into a set of themed materials. The second stage involves explaining the studied phenomenon in the context of existing theory to better understand the larger context shaping the phenomenon.

We began by evaluating the interview transcripts and formal documents to determine the context for coding (Maxwell, 2005). Descriptive codes based on the literature review were created before the interview phase commenced. The goal of coding is to ‘fracture' findings (Strauss, 1987) into categories that permit comparison and thereby facilitate the development of theoretical concepts. Once the interviews were completed, the descriptive codes were considered in terms of the data to explore emerging patterns within that data. The pattern codes permitted the themes identified by the descriptive codes to be elaborated further, enabling more thorough analysis. Initial codes were based on the research questions, which allowed the interview to be conducted analytically and ensured that the coding was linked to the conceptualization of the research.

To reduce researcher bias and enhance the reliability and validity of the study, researchers read the interview transcripts and formal documents several times, and a third, independent researcher double-checked them (Lincoln & Guba, 1985). In addition, multiple data sources (interview transcripts, secondary research and company documents) enabled triangulation of the data and helped mitigate the risk of systematic biases (Maxwell, 2005). Section 4 (Findings) includes the respondent’s relevant interviews (which were quoted verbatim and interpreted) to further improve the study's validity (Eisenhardt, 1989).

4. Findings

4.1. Decision making autonomy

To understand the issues and obstacles facing KC over autonomy and control between global and regional teams, we explored the perceived roles of global and regional marketing team members. Interviewee 3 observed, “The U.S. business is very different from the state of play in India, Turkey or South Africa...[so] there’s...a necessity for...local positioning, but within the umbrella of...some governance around what we want the...brand to stand for". KC's global strategies seek greater alignment of their brand offering, but interviewee 5 admits that “there's probably some standardized processes that our global and regional communicators use, but we're [still] trying to get more aligned and merged”. However, any uniform strategy would, according to Interviewee 7, “…fall apart because [of] the consumer nuances, the language in which you speak about the product. The need states that can be satisfied by the same product can be a wide spectrum of needs”. Since standardization can be perceived as an impediment to innovation and creativity (de Chernatony, Halliburton, & Bernath, 1995), KC's global brand management strategies attempt to reduce mandatory elements, thus allowing the regions to adopt and adapt within a prescribed framework.

Interviewee 4 explained, “…at the end of the day, every market has to do what’s best for them. However, part of the reason why these jobs like mine exist [i.e., a global branding role] within this company is to provide...freedom within the framework. So we have to establish some frameworks ‘because you don’t want...your brands to mean different things in different places’. The KC framework uses various processes and templates to determine what a brand stands for, and allows the markets to “adapt what's relevant for them” (Interviewee 4), thereby giving the regions “almost total autonomy” (Interviewee 3) and creating “powerful regional organization[s]” (Interviewee 10) that have the ability to “pick and choose” (Interviewee 2) the strategies most relevant to their market. This strategy aligns with Thrassou and Vrontis (2006) assertion that marketing strategies should be customized to suit the unique dimensions of each market. Although senior executives lead KC's global brands in roles created by the recent marketing/branding restructuring process, the findings suggest that, given the firm’s organizational structure, the global marketing/branding team lacks the blanket ability to mandate strategies. “My role”, Interviewee 4 clarified, “is to establish what the strategy is and then establish...how each market executes their strategy because every market is in a different place in terms of development of competitive set and so forth. So then we have an overarching strategy in terms of this is [what] we want...and what we want [the] brand to mean. These are our business objectives. These are the innovation platforms that we’re going to work on, and then we translate that down into each market and how each market is going to execute that".
Table 1
Respondent characteristics.

<table>
<thead>
<tr>
<th>Interviewee</th>
<th>Position</th>
<th>Role</th>
<th>Region</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phase 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>*Interviewee 1</td>
<td>Regional Marketing Director</td>
<td>Category/region specific</td>
<td>Southeast Asia — regional</td>
</tr>
<tr>
<td>*Interviewee 2</td>
<td>Senior Brand Manager</td>
<td>Brand/country specific</td>
<td>Southeast Asia — local</td>
</tr>
<tr>
<td>*Interviewee 3</td>
<td>Global Brand Director</td>
<td>Brand specific</td>
<td>Global</td>
</tr>
<tr>
<td>*Interviewee 4</td>
<td>Global Marketing Director</td>
<td>Category specific</td>
<td>Global</td>
</tr>
<tr>
<td>*Interviewee 5</td>
<td>Global Communication Director</td>
<td>All categories and brands</td>
<td>Global</td>
</tr>
<tr>
<td>Phase 2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interviewee 6</td>
<td>Global Digital Director</td>
<td>All categories and brands</td>
<td>Global</td>
</tr>
<tr>
<td>Interviewee 7</td>
<td>Global Brand Director</td>
<td>Category specific</td>
<td>Global</td>
</tr>
<tr>
<td>Interviewee 8</td>
<td>VP of Corporate Innovation</td>
<td>All categories and brands</td>
<td>Global</td>
</tr>
<tr>
<td>Interviewee 9</td>
<td>Global Marketing Operations</td>
<td>All categories and brands</td>
<td>Global</td>
</tr>
<tr>
<td>Interviewee 10</td>
<td>Chief Marketing Officer</td>
<td>All marketing functions</td>
<td>Global</td>
</tr>
<tr>
<td>Phase 3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>*Interviewee 11</td>
<td>VP Global Brands</td>
<td>All categories/brands</td>
<td>Global</td>
</tr>
<tr>
<td>*Interviewee 12</td>
<td>Regional Director</td>
<td>One major category</td>
<td>Regional (Europe)</td>
</tr>
<tr>
<td>*Interviewee 13</td>
<td>Regional Marketing Leader</td>
<td>One major category</td>
<td>Andean region (Latin America)</td>
</tr>
<tr>
<td>*Interviewee 14</td>
<td>Regional Marketing Leader</td>
<td>One major category</td>
<td>Andean region (Latin America)</td>
</tr>
<tr>
<td>*Interviewee 15</td>
<td>Regional Marketing Leader</td>
<td>One major category</td>
<td>Regional (sub-Saharan Africa &amp; Middle East)</td>
</tr>
</tbody>
</table>

*Telephone interview; otherwise face-to-face.

Overall, the interviewees agreed that the global roles focused on applying and transferring global best practices, even though they had no “line of authority over regions or countries” (Interviewee 3). This experience is consistent with Aaker and Joachimsthaler’s (1999) findings that global brand managers and teams often have little authority to mandate the strategies they create. Indeed, Interviewee 3 observed that the global role seemed to be about “influence, suggestion, coercion... [and] negotiation”. Interviewees implied that communicating the value of new strategies and persuading regions to adopt them was a best practice to overcome autonomy issues. To this effect, KC attempted to use brand planning processes and internal brand communication while “...build[ing] relationships and trust within those relationships and confidence in those relationships” (Interviewee 5). Notably, a “spirit of partnership” existed (Interviewee 7), although local resistance, fuelled by a fear of change, occasionally bubbled beneath the surface. Interviewee 1 explained that “there’s that torment of, we want to be on-board and supportive, but we’re also a bit frightened of changing a very successful formula, and don’t want to be forced to do something that we don’t think is as good as what we’re doing now”.

In an attempt to minimize the resistance that regions have towards change (Jain, 1989; O’Donnell & Jeong, 2000), KC nurtures a culture in which best practices can be freely shared without altering the power dynamics of the regional teams. This concept gained general acceptance as a fundamental aspect of the firm’s global brand management. Although all interviewees commented on KC’s commitment to “share [ing] learnings across countries” (Interviewee 2) through ongoing dialogue, some noted that KC “had never been the best at sharing” (Interviewee 1). Thus, KC began changing its approach (notably by creating a global marketing/branding team), which had hitherto focused on “...local execution and some global sharing” (Interviewee 1). The new process collated insights and best practices using a bottom-up strategy in which each market was researched and “individual market insight[s] that [were] consistent across all the markets [were] laddered up to global insight[s]” (Interviewee 4). Interviewee 4 also noted that several common platforms were created from which best practices and insights could be shared. The first of these was the Global Marketing University, which was implemented in 2008. The university involved “…training of the countries on the same tools and template so [that they would] all be talking the same language” (Interviewee 1). In addition to the Global Marketing University, interviewees mentioned other meetings (most of which occurred at the regional level) that focused on sharing best practices, driving innovation, and evaluating marketing campaigns.

Interviewees also identified internal SharePoint websites, such as the global marketing website, as key sources of best practices and other information. However, Interviewee 1 stated that while the lessons from the Global Marketing University were helpful, the university only occurred once a year, leaving the regional teams to implement changes with “no one to go to and no one to help [with] the actual doing”. The interviewee (who had a senior regional marketing role) suggested that senior managers on the global team may need to stay longer and go into more detail or may need to provide “…someone that you can...go to afterwards” to allow for greater usability and adoption of information.

Overall, KC’s decentralized structure did not appear to be problematic or to hinder its global brand management aspirations, despite opinions to the contrary (Levitt, 1983). Instead, global leaders viewed local adaptation (achieved through regional autonomy) as a competitive advantage. As Interviewee 3 explained, “Going up against our competition, we should put that into context as well because our major competitor globally is Proctor and Gamble...and they tend to operate their brand much more globally than we do...We feel like they lose some effectiveness by doing [so], so they’re just not quite as nimble at a local level, and so I think that’s...part of the reason that drives our competitive advantage...part of our competitive advantage that I would not like to see us lose, actually, which might be a little sacrilegious for a...global person to say.” This sentiment is consistent with the argument that global players must find and maintain the right balance between local adaptation and global standardization (Vrontis, Thrassou, & Lamperianou, 2009).

4.2. Balancing global standardization with regional adaptation

KC is attempting to “get as many synergies and efficiencies as [it] can without subjecting itself to a one-size-fits-all view of the world” (Interviewee 11). This method of change management aims to imbue the fundamentals of global branding in the regional teams, thereby increasing their adoption of best practices. Starting with its core brands, KC’s global team completed segmentation studies on six key markets whose regional leaders volunteered for the process. This segmentation work “established global strategic targets, consumer targets, and target audiences, and illustrated key target segment characteristics in various geographic locations” (Interviewee 11). Thus, with a consensus process similar to the one already used inter-regionally, the global brand team “prioritized [consumer]
needs” and created a global brand promise and associated architecture. With the same strategic plan in mind, regional leaders then adapted these promises and architectures to create a more regional focus based on local market opportunities. This process combined “bottom-up local market insights and requirements and ideas with...top-down strategic assessment of the brands’ problems and opportunities” (Interviewee 12).

The introduction of a global team (the majority of whose members had had less than three years of tenure at KC, while the senior regional employees had spent decades in the organization) created “a lot of angst and friction and reaction[s] of fear” in the regions. In an organization with immense regional autonomy, a (perceived) shift to a more centralized structure generated internal resistance (Schultz & Hatch, 2006), particularly because the introduction of voluntary processes prompted the resignations of senior employees, or “legacy leaders”, who “weren’t aligned” with the new structure. This was, however, perceived to be more beneficial than “running in a fragmented approach or worse yet...having one of the regions or one of the clusters driving the others.” Within KC, the issue did not appear to be based on autonomy or power. Instead, the challenge was how to increase regional alignment. Interviewee 9 stated, “Synchronization is a big challenge in a company that never had this before, where each of these regions is run like a franchise”.

The purpose of establishing global branding fundamentals was thus to “change people’s perspectives” so that they became more brand driven and used the “right analytics before making decisions”. Therefore, if data were used as a guide for regional decision making, the findings from global studies and the results from global best practices would be enough to increase strategy adoption. However, research budgets are limited, and the “sit on the side line and cherry pick” attitude remains prevalent, particularly in the countries that were not part of the global studies. A global mindset is required to overcome this attitude, a mindset that increases the degree to which people opt in and requires an exception to opt out. This is consistent with Heiden’s (2007) argument that MNCs should empower subsidiaries by giving them greater autonomy while using centralized strategies to enhance consistency and corporate compliance. Thus, without any distinct plans to reduce the autonomy of the regions, KC is seeking greater alignment and adoption with “mechanisms to drive compliance”, such as standard brand measures that allow for regional comparison and modifications to employee objectives and remuneration.

4.3. Building regional marketing capability

Interviewee 12 saw the underlying tenant of the current global brand strategy as being less about the standardization issue itself and more about building regional marketing capability and elevating the marketing function within the organization globally. In fact, Interviewee 12 commented that KC’s CMO challenged and inspired regional marketers “to do great work”. This view matches the practice of facilitative leadership, where managers promote critical thinking and act as mentors or coaches to improve employee capabilities (Simionin & Özsomer, 2009). According to Simonin and Özsomer (2009), however, facilitative leadership is typically insufficient in disseminating knowledge among subsidiaries. Nevertheless, other manifestations of a firm’s commitment towards developing a knowledge-sharing culture, such as instituting formal mechanisms and processes for knowledge dissemination, can encourage knowledge transfer and sharing (Simionin & Özsomer, 2009). Consistent with this notion, Palmer introduced rigorous new marketing processes and disciplines (such as the aforementioned Global Marketing University and standardized brand metrics) and created a culture of sharing whereby regions submit their best work for peer review. If a regional office has a genuine need to deviate from global strategy and a genuine capability to execute great marketing, the Global Sector Leadership team will empower it to act more independently. Otherwise, the regional office will be strongly encouraged to share and borrow from global best practices. Interviewee 13 explained that this approach worked because the creation of a respectful relationship based on influence meant that all levels of the organization needed to pitch ideas, which resulted in the co-construction of global strategy and the avoidance of a rigid framework.

4.4. Summary

Our findings explicate how KC has implemented numerous changes to become a global marketing organization. According to Interviewee 10, KC’s global brand management did not appear to be about control and influence: “…control in this environment, in this world, is completely overvalued. It is all about influence and inspiration and getting people to do it because they want to...You’ve got to inspire them and lead them to do it...”. With this sentiment rooted in its management philosophy, KC is seeking to strike the right balance between “multiple market development and local inspiration” (Interviewee 8). Interviewee 15 added that, as in all matrix structures, regional marketing leaders must be good influencers. They do, after all, perform staff functions, not line functions. Finally, Van Gelder (2003) contends that firms should standardize global brands by inspiring, not upsetting, local managers, an argument reiterated by Palmer.

The success of KC’s global brand management strategy depends on balancing consistency with regional decision making autonomy. It is, notes Interviewee 8, about “delivering new benefits...in multiple markets with similar positioning, similar communication, similar product formats” without losing its local footprint or global dominance. Interviewee 7 explained that balance can be achieved by “satisfying real, un-met consumer needs on a local level...Meeting those local-level needs and then aggregating them up and looking for commonalities that might then become a global mindset and a global platform”. Such balance, Interviewee 7 believes, will occur through a non-systemic, evolutionary change, assisted by global brand teams that act as “great facilitators”. The balancing point between global standardization and local adaptation is dynamic; organizations are “living organisms that transfer knowledge and grow in capability” (Interviewee 10), and organizations such as KC should be designed to meet changing consumer needs.

Is KC’s new global brand strategy working? Preliminary evidence suggests that recent marketing strategy changes have indeed resulted in superior financial performance. For example, after KC improved the dissemination of regional insights within the firm, its North American division adopted successful brand strategies from Israel and Australia, a move that increased United States market share in the associated product lines vis-à-vis KC’s chief competitor, Proctor and Gamble (Neff, 2011). More generally, a recent independent financial analysis predicted that KC would experience sustained financial growth in the coming years, due in part to the improved sales growth of its brands (Levy, 2011). The early evidence confirms that recent changes in the firm’s global brand management process have enhanced its performance.

5. Discussion

Our findings show that balancing standardization and global best practices with regional empowerment and capacity-building is paramount to KC’s global brand management strategy. The key to understanding the KC experience lies in deconstructing this strategy. We mapped this process in Fig. 1 and drew on transformational leadership theory and dynamic capability theory to explain how and why KC’s strategy works, thereby laying the foundation for a global brand management process theory to inspire future research and practice.

5.1. Theoretical implications

In reference to Fig. 1, the KC global brand realignment process began with the strategic review initiated by Tony Palmer when he was appointed CMO (with the obvious backing of a more “market-oriented"
Transformational leadership and inspiring regional managers to support and direction through well-crafted processes, while leveraging the company's global scope and scale to provide centralized new type of global marketing organization, one which simultaneously leadership/board_of_directors.aspx). Palmer articulated a vision for a board; see http://www.kimberly-clark.com/ourcompany/overview/

In truth, we didn’t change much. It’s more about better systems based in Europe) noted that turmoil and loss of momentum). Interviewee 11 (a global executive (Interviewee 12). Strategic leadership theory suggests that buy-in from all levels of management is vital to innovation and sustained success. Indeed, Elenkov, Judge, and Wright (2005) emphasize the need for visionary leadership, inclusion, reward, and the intellectual stimulation of staff. In addition, Jansen, Vera, and Crossan (2009) demonstrate the impact of transformational leadership on innovation, which captures many of the facets of cooperation and coordination present in the KC case. In short, KC’s head of establishment of the Global Sector Leadership (GSL) team, a high-level oversight committee that sits outside of the existing organizational structure. This team reports to the CMO and to two group presidents, ensuring that regional proposals are on strategy. A region that wishes to pursue an initiative that is not on strategy would need to secure agreement from the CMO and the group presidents (but even then, the GSL team may not provide resourcing support), producing a form of accountable and qualified decentralization in the process.

The new KC strategy and processes were designed and implemented as part of an ongoing effort to extend its brand-building and marketing capabilities, accelerate growth and product innovation, and improve the effectiveness of their marketing resources (speed to market and success rates). This requires dynamic organizational and strategic routines through which firms can achieve new resource configurations as markets emerge and evolve (Eisenhardt & Martin, 2000). While one stream of literature posits that dynamic capabilities are directly associated with organizational performance, a second stream argues that dynamic capabilities are important to the development of new capabilities, which, in turn, improve organizational performance (Helfat & Peteraf, 2003; Zahra, Sapinenz, & Davidsson, 2006). The KC experience exemplifies this second stream. Through global sharing and collaboration, KC is building local capabilities and empowering regional managers to execute the best possible marketing strategies. By becoming more agile (Chonko & Jones, 2005), innovative, and resourceful, KC should be able to operate more profitably in a rapidly changing and fragmenting global marketplace (Tsourveloudis & Valavanis, 2002). Agility, after all, means having the organizational support, resources, and intellectual capital necessary to deal with change (Chonko & Jones, 2005), which KC’s new global brand strategy and processes aim to achieve.

5.2. Managerial implications

On some levels, KC’s global brand management is neither new nor revolutionary. For instance, in 2001, Unilever split responsibility for each of its brands between two groups: a brand development group, which had a global scope, and a brand-building group, which was charged with building the brand in the specific markets and major regions in which Unilever operated (Deighton, 2007). The difference between Unilever and KC is not in the strategic plans, but in the processes and implementation. To paraphrase Bertolt Brecht (Mother Courage), the finest plans are spoiled by the littleness of those that carry them out [regionally]; even [CMOs] cannot execute
them all by themselves. Transformational leadership must achieve widespread buy-in before implementation can proceed and succeed. We saw this at KC. Other MNCs may be willing to restructure in an effort to produce immediate and measurable changes, but KC focused first on achieving buy-in, then on building local capacity through better marketing processes, and finally on empowering regions to grow. It should be noted, however, that many of KC’s subsidiaries were late market entrants relative to KC’s chief competitors, Unilever and Proctor & Gamble. Indeed, by virtue of their longstanding presence in numerous international markets, Unilever and Procter & Gamble have already experienced success (and mistakes) in their efforts to enhance global standardization and centralization.\textsuperscript{1} The processes that KC implemented should therefore be viewed in the context of the firm’s status as a latecomer to brand standardization.

5.3. Limitations and directions for future research

This study examined the interplay between KC’s regional offices and global headquarters. It devoted less attention to analyzing the role of the local subsidiaries in this relationship. The ways in which local subsidiaries respond to increased centralization and global standardization is therefore an important area for future research, as a breakdown in communication along the global–regional–local chain could mean that regional or global best practices are not adequately transferred to the local level.

By establishing the fundamentals of global brand management in all regional teams, KC has ensured that its branding teams are “singing from that same songbook” or “singing the same thing” (various interviewees). However, balancing regional autonomy and standardization strategy is difficult, KC must determine how it can maintain consistent brand meaning while allowing a diverse customer base to adapt its brands to local customs.

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Appendix 1. Interview protocol

Grand tour Question 1: What is your understanding of the new global brand management approach that Tony Palmer and his team have implemented? What do you like/dislike about it and why?

Research Question 2: How, if at all, does Kimberly-Clark attempt to balance centralized coordination of marketing strategies with local implementation? Are marketing and branding strategies standardized (globally) or adapted (locally) to suit each market? If so, how? How well is this working?

Research Question 3: How much decision making authority/autonomy do local managers have? How do they feel about that?

Interviewer prompts (albeit seldom referred to)

- Briefly describe your current role at KC and any other previous roles at KC or elsewhere.
- What is your understanding of the term “global brand”?
- How are KC brands currently managed locally and globally?
- How does KC define global branding?
- How important is global branding to your SBU?
- What do you understand “global brand management” to mean?
- What is KC’s global branding strategy, and how is it implemented?
- How are strategies communicated within KC?
- How are best practices communicated/shared within KC?
- Is consistency important in the KC global brand management processes?
- In your opinion, is the global branding strategy understood across the various regions?
- Is the global branding process consistent across different regions and different product categories?
- Is there a system that KC uses to evaluate the performance of the global brands and the global brand management process?
- What role do you (your team) play in the global brand management process?
- Who is responsible for developing global brand strategies? Who is responsible for implementing global brand strategies?
- What role do senior leaders play in the global brand management process?
- What role do local or country-specific managers play in the KC brand management process?
- To what extent are global brand strategies understood throughout the organization?
- What autonomy do local/regional marketing teams have over brand management strategies?
- How would you describe the global branding structure of KC? Of your SBU? Does this differ from the overall marketing structure?
- Who is involved in the development of brand strategies?
- Who is involved in the articulation and implementation of brand strategies?

Phase 3

Grand tour question: Have you been given some background on our study? Of the 10 people we have spoken to, only two have regional/local roles. We are therefore interested in getting more “non-global” (i.e., regional/local) insights. From your perspective, in your market(s), what do you like/dislike about the new global brand management strategy and why?

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\textsuperscript{1} We thank Aysegül Özsomer for this astute insight.
Generating global brand equity through corporate social responsibility to key stakeholders

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ABSTRACT

In this paper, we argue that corporate social responsibility (CSR) to various stakeholders (customers, shareholders, employees, suppliers, and community) has a positive effect on global brand equity (BE). In addition, policies aimed at satisfying community interests help reinforce the credibility of social responsibility policies with other stakeholders. We test these theoretical contentions by using panel data comprised of 57 global brands originating from 10 countries (USA, Japan, South Korea, France, UK, Italy, Germany, Finland, Switzerland, and The Netherlands) for the period from 2002 to 2008. Our findings show that CSR toward each of the stakeholder groups has a positive impact on global BE. In addition, global brands that follow local social responsibility policies in communities obtain strong positive benefits through the generation of BE, enhancing the positive effects of CSR toward other stakeholders, particularly customers. Therefore, for managers of global brands, when generating brand value, it is particularly effective to combine global strategies with the need to satisfy the interests of local communities.

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1. Introduction

Global brands exist in multiple markets, including the financial services, telecom, and fast-moving consumer goods markets. Many firms, such as Unilever, have clearly started to focus more on building strong global brands than on building multiple (strong) local brands (Kumar, 2005). A strong corporate social responsibility (CSR) record is expected from these global brands (Holt, Quelch, & Taylor, 2004). The implementation of a CSR policy may generate a trusting relationship between the company and stakeholders that causes stakeholders to become committed to the organization through actions such as customer loyalty, stockholder capital investments, and supplier investments (Garbarino & Johnson, 1999; Maignan & Ferrell, 2004; Sen, Bhattacharya, & Korschun, 2006). In the global marketplace, a firm’s social and environmental track record and its treatment of employees are considered to be very important trust issues (Edelman, 2008).

However, it is frequently stated that global brands do not have strong CSR records, and they are accused of predatory behavior (Connor, 2001). Building up CSR reputations is difficult for global brands, as global brands have to build local CSR reputations through local relationships while also demonstrating global social responsibility (Polonsky & Jevons, 2009). Moreover, the CSR practices of global brands are typically perceived as being self-interested, which may reduce their effects on brand equity (BE) (e.g., Prout, 2006; Yoon, Gurhan-Canli, & Schwartz, 2006). Specific examples have shown the relevance of CSR for global brands. BP’s considerable problems with their local oil operations in the Gulf of Mexico near Louisiana has strong global repercussions for the global BP brand (Ritson, 2010). Coca-Cola was faced with customer protests in the UK and the USA because of what was considered to be a poor environmental record in India and allegations of human rights violations in Columbia (Hills & Welford, 2005). Moreover, the global presence of brands and their operations may even cause the CSR policies of brands and their operations may even cause the CSR policies of national CSR toward boost sales (Knight & Greenberg, 2002). However, the anti-sweatshop movement believes that Nike is hypocritical, as Nike has been accused of exploiting young female migrant workers in the developing world to produce its products and only using its promotional CSR toward boost sales. (Knight & Greenberg, 2002). Similar arguments appear in the study by Wagner, Lutz, and Weitz (2009), who point out the negative reactions of consumers toward reactive CSR strategies that try to mitigate harm after an irresponsible action has been reported. The Nike case also points to a complicating issue, namely that CSR involves activities that focus on multiple
stakeholders, including customers, employees, shareholders, and community in which the credibility of CSR policies will play a pivotal role in the efficient implementation of CSR initiatives. Firms, therefore, need to understand whether and how their multi-faceted CSR efforts have an impact on their global BE.

Within the academic literature, there is a vast amount of research on the effects of CSR on brand performance metrics such as brand evaluations, brand loyalty and firm performance (e.g., Du, Bhattacharya, & Sen, 2007a; Klein & Dawar, 2004; Luo & Bhattacharya, 2006; Orlitzky, Schmidt, & Rynes, 2003). However, studies on CSR and global brands are scarce. Holt et al. (2004) emphasize the importance of CSR as a means of differentiation for global brands, while Polonsky and Jevons (2009) discuss global branding and CSR in a qualitative manner. In-depth case studies have described CSR issues for global brands such as Nike and Coca-Cola (e.g., Hills & Welford, 2005; Knight & Greenberg, 2002). Research in business ethics has also discussed the relevance of CSR toward global firms and has considered research on CSR from a global perspective (e.g., Arthaud-Day, 2005; Manakkalathil & Rudolf, 1995; Prout, 2006). However, we could not identify any studies that explicitly studied the relationship between a global brand’s CSR efforts and global BE in an international setting.

The key research question in this study concerns the investigation into the effects of CSR practices with different stakeholders on global BE, with an emphasis on the role played by credible CSR initiatives. We first investigate whether CSR efforts impact global BE. Second, we aim to assess which CSR efforts have the strongest effects on global BE. We hypothesize that CSR aimed at community and customers will have stronger effects on global BE, than CSR directed at other stakeholders. Third, we investigate the potential moderating role of CSR toward community, which confers credibility to CSR initiatives, on the impact of CSR toward different stakeholders on BE.

We address these issues using panel data from 57 global brands originating in 10 countries (the US, Japan, South Korea, France, the UK, Italy, Germany, Finland, Switzerland, and The Netherlands), as included in the 2002–2008 Sustainalytics Global Profile (SGP) database. Each firm’s CSR profile contains items that address major stakeholder issues. We complement the database with global BE information obtained from Interbrand. Our econometric approach allows us to assess potential long-term effects through the inclusion of a lagged BE term in our model. Hence, we also discuss potential long-term effects of CSR on global BE.

The contributions of this study are threefold. First, although prior theoretical arguments justify the connection between CSR and BE, we provide the first empirical study addressing this issue at an international level. Second, this study explicitly examines the differential effects of CSR efforts with different stakeholders on global BE, in which we specifically focus on the important role of CSR efforts to community and customers. Last, we contemplate the interaction effects between community satisfaction and different CSR dimensions in the generation of brand value.

The remainder of this paper is organized as follows. We will first discuss our theoretical underpinnings and the derived Hypotheses. Then, we will describe our data and the econometric model used. The modeling results are discussed subsequently and we end with a conclusion, a consideration of managerial implications, and a discussion of our research limitations and resulting future research directions.

2. Theoretical underpinnings and hypotheses

2.1. CSR and brand equity

CSR has gained attention in multiple disciplines including marketing, management, strategy, and business ethics. A relatively broad definition of corporate social responsibility is “the company’s status and activities with respect to its perceived societal obligations” (Brown & Dacin, 1997, p. 68). Its broad nature implies that CSR also involves multiple initiatives relevant to multiple stakeholders, e.g., community support, employee support, and diversity (Sen et al., 2006).

For brand management, firms need a strong understanding of what is driving BE. Keller and Lehmann (2006) consider three distinct perspectives for studying BE: a (1) customer–based, (2) company–based and (3) financially-based perspective. In this study, we use the Interbrand measure for our measurement of global BE. This measure, which is discussed in greater detail in our Methodology section, is frequently used in marketing (e.g., Madden, Fehle, & Fournier, 2006). The Interbrand measure has a rather broad perspective as it involves both a financial and a customer perspective, although it is not free from criticism (Madden et al., 2006).

2.2. Effect of CSR on brand equity

Although there are multiple studies that examine CSR outcomes, no study has yet investigated the effect of CSR on global BE. We expect CSR to positively affect global BE. Given that our BE measure involves both a customer dimension and a financial dimension, we use two lines of reasoning to determine why this effect may occur. First, CSR may affect customer brand preferences and customer loyalty (e.g., Bhattacharya & Sen, 2004; Du et al., 2007a; Orlitzky et al., 2003). Second, CSR may affect the financial performance of a brand (Luo & Bhattacharya, 2006).

Within the popular marketing literature, it is generally acknowledged that CSR should positively affect customers’ brand perceptions (e.g., Rust, Zeithaml, & Lemon, 2000). Importantly, Holt et al. (2004) argue that social responsibility is an important driver of global brand evaluations. However, the driving role of CSR with customers for BE depends on the credibility of such policies. Multinational companies that market global brands are often accused of seeking to maximize their corporate profits without much regard for the needs of the poorer and weaker societies in which they operate, e.g., Nike’s sweatshop labor and Coca-Cola’s alleged water exploitation (Hills & Welford, 2005; Knight & Greenberg, 2002). Such problems may appear in visible CSR initiatives that are connected to benefit salience (Yoon et al., 2006), in which firms are believed to use CSR only for their own self-interest (Prout, 2006). Hence, in this situation, it is important to achieve credibility in CSR initiatives to ensure effectiveness in the implementation of CSR policies that are connected to firms’ core businesses (Yoon et al., 2006).

Within the marketing literature, there is ample evidence that customer beliefs concerning CSR affect individual customer outcomes such as brand preference, brand loyalty and positive word-of-mouth. Evidence is also provided by Hoeflfler and Keller (2002) and Keller (2003), who report that corporate social marketing can enhance customer brand metrics such as brand awareness, brand image, brand credibility and brand engagement. Lichtenstein, Drumwright, and Braig (2004) showed that customers of a grocery chain that has stronger CSR beliefs tend to be more loyal to that chain. In the same vein, Du et al. (2007a) report that visible CSR leads to stronger brand identification, brand loyalty and brand advocacy. Recently, Vlachos, Tsamakos, Vrechopoulos, and Avramidis (2009) showed associations between CSR and repeat patronage intentions and recommendation intentions. This type of customer loyalty connected to CSR acts as an implicit brand insurance, which is particularly valuable for global brands that are subject to changing social expectations, affluence, and globalization (Werther & Chandler, 2005).

These authors state that “CSR is about incorporating common sense policies into corporate strategy, culture, and day-to-day decision making to meet stakeholders’ needs, broadly defined. It is about creating strategies that will make firms and their brands more successful in their turbulent environments. Stripped of the emotionalism and name calling, we see
strategic CSR as global brand insurance". Remarkably, given the risks that controversies in one subsidiary of a global brand may affect the full organization, it is particularly relevant for such global brands to be perceived as credible organizations in terms of CSR policies. Being labeled as socially responsible organizations will prevent local problems from negatively affecting the entire organization, which may seriously damage a global brand image. Hence, all of these studies support the positive main effects of CSR on multiple customer brand metrics, particularly for global brands.

Our second line of reasoning concerns the link between CSR and a brand's financial performance. Orlitzky et al. (2003) theorize on two potential ways in which CSR may affect financial performance. The first is through the improvement of capabilities and competencies within the firm. Building on the resource-based view of the firm (Barney, 1991), they argue that CSR requires and thus improves managerial competencies such as improved scanning skills, processes and information systems, which increase the organization's preparedness for external changes, turbulence, and crisis. Such competencies are particularly relevant for managing global brands, as these operate in different environments. The second way concerns the improvement of a firm's reputation among its stakeholders. Specifically, CSR, when credible, may build a positive image among customers (as discussed above), investors, banks, and suppliers (Fombrun & Shanley, 1990; Sen et al., 2006). In such a setting, customer loyalty increases, thus enhancing firm value. In addition, credible CSR initiatives reduce information asymmetries and monitoring needs, which are particularly acute in large and complex organizations, which are the organizations that typically support global brands (Zajac & Westphal, 1994). The reduction in such information asymmetries will favor non-customer stakeholders making costly firm-specific investment by providing valuable resources that will in turn generate BE. In their meta-analysis, Orlitzky et al. (2003) show a positive correlation between CSR and financial performance.

In short, the above discussion demonstrates that there is ample evidence that CSR, particularly when visible and credible, can affect customer brand metrics and financial brand performance metrics. Hence, we formally hypothesize the following:

**H1.** CSR positively affects global brand equity.

**2.3. Differential effects of CSR initiatives to different stakeholders**

In our discussion of the primary effect of CSR on BE, we consider CSR as one broad, overarching construct. However, as already noted, CSR involves multiple initiatives to different stakeholders (Sen et al., 2006). In this study, we specifically distinguish CSR initiatives to community, customers, shareholders (labeled as corporate governance), employees, and suppliers. These five stakeholders are frequently mentioned as being important in different studies on CSR (e.g., Bhattacharya & Sen, 2004; Orlitzky et al., 2003; Sen et al., 2006). Thus far, no studies have explicitly studied the differential effects of CSR initiatives on these different stakeholders. However, the meta-analytic results of Orlitzky et al. (2003) suggest differential effects between CSR initiatives. They specifically report that philanthropic donations aimed at community were more strongly related to financial performance than all other CSR initiatives studied.

Wood and Jones (1995) argue that differential effects of CSR initiatives on performance may occur because the expectations and evaluations of CSR may differ from one stakeholder group to another. They further argue that there should be no mismatch between the CSR stakeholder measures used and the studied outcome measure. Hence, they suggest the existence of a positive relationship between CSR initiatives to market-oriented stakeholders (i.e., customers) and market measures. Applying this reasoning to our study, one could argue that CSR initiatives relevant to customers should have a stronger effect than other CSR initiatives on our global BE measure, which is partially based on customer metrics. In line with this, Bhattacharya and Sen (2004, p. 14) argue that companies need to identify what customers consider to be CSR-related activities and devote the necessary resources such activities.

An additional explanation for the differential effects is based on visibility reasoning. CSR initiatives may differ in their visibility (Burke & Logsdon, 1996). While initiatives to customers may be rather visible in the marketplace, initiatives to internal stakeholders (i.e., employees) and external stakeholders higher up the supply chain (i.e., suppliers, investors) will be less visible to consumers. Moreover, such differentials in visibility are amplified in global brands, given that they are closely monitored by the mass media (Climard & Yeager, 2006). Prior research has acknowledged the importance of CSR awareness. Du et al. (2007a, p. 238) explicitly state “CSR awareness, or the lack thereof, is a key stumbling deficiency in most CSR strategies” (see also Bhattacharya & Sen, 2004; Du, Bhattacharya, & Sen, 2010; Maagign & Ferrell, 2004; Maagign & Ralston, 2002). However, the visibility of CSR initiatives may be less beneficial to the brand when CSR initiatives are related to the company’s business (e.g., a cigarette producer sponsoring a cancer fund), increasing the salience of firm-serving benefits (Yoon et al., 2006). To eliminate these backfire effects, the combination of visible CSR initiatives directed at customers and credible CSR not directly related to a firm’s core business is of particular value. One example of the latter type of CSR initiative is CSR toward community. In this line, after studying the results of a CSR initiative focusing on community of Crest toothpaste, Du, Bhattacharya, and Sen (2007b) show that this initiative builds credibility and customer loyalty that, in turn, enhance brand value.

A last line of reasoning is based on Granovetter’s (1983) analysis, which suggests that distant connections among units in a large organization (those of global brands) are more informative than strong connections in explaining a firm’s behavior. A firm’s actual ethical commitment can be inferred from its behavior in regard to its loosely connected stakeholders in terms of direct interests, e.g., local communities. Such (secondary) stakeholders are distant from the interests of global brands’ headquarters, which may function as a more credible signal of lack of self-interest.1 The consequence is that CSR in communities should have a significant effect on the generation of BE through customers’ decisions, particularly when combined with visible CSR to customers, given that customers are increasingly conscious of buying products from firms that follow a credible CSR policy (Christmann, 2004).

Based on the above visibility and credibility rationales, we expect that CSR initiatives to customers and community should have a stronger effect on BE than initiatives to suppliers, investors, and employees. However, we emphasize that we do not expect null effects from these latter initiatives. As discussed in our previous section, CSR initiatives to any stakeholder group create a firm’s competitive advantage through stakeholder provision of valuable intangible resources; that is, in turn, create firm value (Orlitzky et al., 2003; Sharma & Vredenburg, 1998). In addition, improved reputations among employees, investors, and suppliers may benefit the firm (e.g., Kaufman, Jayachandran, & Rose, 2006; Langerak, 2001; Orlitzky et al., 2003; Srivastava, Shervani, & Fahey, 1998). We thus hypothesize as follows:

**H2.** CSR initiatives to community, customers, investors, employees, and suppliers each have a positive effect on global brand equity.

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1 Godfrey, Merrill, and Hansen (2009) differentiate between two types of stakeholders: primary, who are essential to the operation of the business, and secondary, who can influence the firm’s primary stakeholders. In particular, customers, employees, suppliers, and shareholders constitute primary stakeholders, and broader groups, such as community, constitute secondary stakeholders (Clarkson, 1995; Greenley, Hooley, & Rudd, 2005; Mitchell, Agle, & Wood, 1997).
H3. CSR initiatives to community and customers have a stronger effect on global brand equity than CSR initiatives to investors, employees, and suppliers.

2.4. Moderating role of CSR toward community

Previous research has emphasized the importance of implementing a credible CSR practice to ensure that CSR attracts the attention of different stakeholders (Lewellyn, 2002; Logsdon & Wood, 2002; Mahon, 2002). CSR practices geared toward community undoubtedly satisfy the firm’s credibility (Du et al., 2007b; Vlachos et al., 2009), as these initiatives clearly go beyond the direct interest of the firm. In addition, as mentioned, a firm’s real commitment in maintaining a CSR policy to different stakeholders can be most clearly inferred from a firm’s relationship to distant units (Granovetter, 1983), over which the direct interest of a firm is less clear, as is particularly applicable in the case of global brands. We can identify secondary stakeholders such as local communities as “distant” stakeholders in regard to the interests of headquarters in global brand multinationals, whereas CSR policies to customers could be considered as having a direct relevance for the firm by creating more satisfied customers, for example. Remarkably, the credibility of CSR toward community is not only important for visible CSR initiatives such as those directed at customers but also for “internal” stakeholders such as employees and suppliers. These stakeholders will be more willing to make specific investments to provide valuable intangible assets when a firm has built a reputation of credibility in social issues. In these firms, the hold-up problem related to firm-specific investments is less acute. The above reasoning applies particularly to global brands, as the organizations that support them are large and more likely to suffer information asymmetries that require intensive monitoring (Zajac & Westphal, 1994). These asymmetries are the basis of agency problems preventing the aforementioned firm-specific investments. Thus, the effectiveness of CSR initiatives to other stakeholders will increase when firms, particularly global brands, have implemented CSR practices to community. Other stakeholders will then develop a sense of fairness, which generates credibility for CSR initiatives (Geyikskens, Steenkamp, & Kumar, 1998; Sen et al., 2006; Vlachos et al., 2009), proving their effectiveness. CSR in community intended to generate trust in other stakeholders fits global brands particularly well. For these firms, a strategy of integrating perceived brand globalness with the development of local symbols through relationships with local communities leads to a more profitable strategy than a pure global standardization strategy (Alden, Steenkamp, & Batra, 2006).

Based on the above reasoning, we propose that CSR initiatives to community will reinforce the positive effects (positive moderation) of CSR toward other stakeholders. Note that such a credibility argument in relation to communities is particularly important for global brands, given the risks they bear from controversies in a subsidiary of their network affecting the overall organization. As extensively discussed by Knight and Greenberg (2002), Nike’s negative social performance toward employees in developing countries might damage its overall reputation; hence, it is particularly important for such global brands to establish credible community-oriented CSR. We thus hypothesize the following:

H4. Firms’ CSR initiatives to community positively moderate the effects of CSR toward other stakeholders (customers, shareholders, suppliers, and employees) on global BE.

3. Data set

Our sample combines panel data from two databases. The first is the SGP database (formerly SiRI Pro), which is the largest publicly available international database specializing in the analysis of socially responsible investments in Europe and North America. The SGP database provides information on 199 items that address major stakeholder issues, e.g., community involvement, customer policies, employment relations, corporate governance, supplier relations, ethical issues, and controversial activities. The data come from interviews by Sustainalytics specialists. The second database is Interbrand, which provides information on the global BE of the most valuable companies (see http://www.interbrand.com). Combining both databases leaves us with an unbalanced panel data of 57 global brands from 10 different countries for the period 2002–2008. The initial unbalanced panel of 357 observations is reduced to 243 because we lose 2 years (114 observations), as we lag the dependent variable by one period to study long-term effects. The second year is lost in the instrumentation of the endogenous variables, given that we take instrumental variables that are constructed using specifications that include up to 2 lagged variables (see the Methodology section). In the final sample, there is an average of 4 observations per firm. Such a figure ensures that the panel is relatively balanced.

The distribution of the 57 firms and 243 observations among countries is as follows: the United States (35 firms and 145 [59.67%] observations), Germany (6 firms and 26 [10.70%] observations), Japan (6 firms and 26 [10.70%] observations), France (3 firms and 13 [5.35%] observations), the United Kingdom (2 firms and 8 [3.28%] observations), Switzerland (1 firm and 5 [2.06%] observations), Finland (1 firm and 5 [2.06%] observations), Korea (1 firm and 5 [2.06%] observations), Italy (1 firm and 5 [2.06%] observations), and The Netherlands (1 firm and 5 [2.06%] observations). In terms of distribution among the sectors (one-digit Standard Industrial Classification [SIC]), the frequencies are as follows: mining and construction (SIC=1): (1 firm and 4 [1.65%] observations); manufacturing of tobacco, beverages, printing, and chemicals (SIC=2): (16 firms and 68 [27.98%] observations); manufacturing of metal, machinery, electronics, and optics (SIC=3): (26 firms and 111 [45.68%] observations); public services, e.g., transportation, radio, television, electric, gas, and sanitary (SIC=4): (4 firms and 17 [7.00%] observations); wholesale and retail trade (SIC=5): (4 firms and 17 [7.00%] observations); services (SIC=7): (5 firms and 22 [9.05%] observations); and public administration (SIC=8): (1 firm and 4 [1.65%] observations).

3.1. Variables

We measure the dependent variable, Brand Equity (BE), with the Interbrand score. Interbrand’s method for valuing global brands consists of three analyses: financial, role of brand, and brand strength analyses. The financial analysis forecasts current and future revenues attributed to the branded products, less the costs of doing business (e.g., operating costs, taxes) and intangibles (e.g., patents, management strength), to assess the portion of earnings due to the brand. The role of the brand constitutes a measure of how the brand influences customer demand at the point of purchase. Finally, brand strength provides a benchmark of the brand’s ability to secure ongoing customer demand (loyalty, repurchase, and retention) and sustain future earnings, which translates branded earnings into net present value. This assessment provides a structured way to determine specific risks to the global brands’ strength.4

Keller and Lehmann (2003, 2006) divide existing measures of BE into three categories: customer mind-set, product market, and financial

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2 For further information on the SGP database, see http://www.sustainalytics.com/.
3 The complete panel would have included 399 observations. The number of observations reduced to 357 because for 14 firms, values are missing for different years in some of the variables needed to estimate our specifications, mainly the variable on R&D.
4 From 2007 on, the weights of the seven components on which the BE measure relies are rebalanced: leadership, stability, support, protection, market, trend, and international. To account for this discontinuity in the methodology, we include a dummy variable in the estimations that equals 1 for the years beyond or equal to 2007 and 0 for the years before 2007. In addition, we estimate a specification (1) to separate the sample into two subperiods (2002–2006 and 2007–2008). The results remain consistent. Further details on the methodology to compute the BE are available at http://www.interbrand.com.
The independent variables include CSR practices geared toward a range of stakeholders: community, customers, employees, suppliers, and shareholders. As proxies for community, customers, corporate governance, employees, and suppliers, we compute the weighted average of those items, as shown in Table 1. The weights are sector-specific and are determined by SGP analysts. They take into account the potential negative effect of a firm's operations in the different items of stakeholders' interests. Once normalized, the result is a continuous-type variable between 0 and 100%.
consideration the potential negative effect of a firm’s operations in the different items of each stakeholder. The weight is assigned in proportion to this potential. Once normalized, the result is a continuous-type variable between 0 and 100%.6 The SGP database also provides an overall rating on CSR by weighting the score of the different stakeholders (see Appendix A for an example of how these scores are computed). The resulting score is a proxy for the firm’s overall dedication to the implementation of socially responsible policies.

We include return-on-assets (ROA) and research and development (R&D) as controls (Chu & Keh, 2006; McWilliams & Siegel, 2000);2 risk as it relates to a firm’s leverage (Rego, Billett, & Morgan, 2009); and Size, which is a proxy for a firm’s visibility, as BE value is connected to a firm’s visibility (Godfrey et al., 2009). See Table 1 for definitions.

3.2. Methodology

We test our Hypotheses by relying on a specification that explains global BE value in terms of the different dimensions of a firm’s CSR and a set of control variables. In particular, we consider the following specification, which also includes interactive terms, to test Hypothesis H4:

\[
\text{Brand Equity}_{it} = \beta + \text{Brand Equity}_{i,t-1} + \alpha_2 \text{Community}_{it} + \alpha_3 \text{Employees}_{it} + \alpha_4 \text{Customer}_{it} + \alpha_5 \text{Corporate Governance}_{it} + \alpha_6 \text{Suppliers}_{it} + \alpha_7 \text{R&D}_{it} + \text{Controls(Sector, Year, Country)} + \eta_i + \epsilon_{it}
\]

where \(i\) and \(t\) index firm and year, respectively; controls (Sector, Year, Country) are a set of dummy variables that capture temporal, sector, and country effects; \(\eta_i\) is the possible firm-specific component of the error term; and \(\epsilon_{it}\) is the error term.8

This specification has three caveats. First, a correlation might exist between the unobservable firm-specific error term \(\eta_i\) and some of the explanatory variables (fixed-effect problem). For example, the characteristics of the manager (which are time invariant) may influence the CSR policy and the global brand value. In this case, the relationship between CSR policies and global BE would be spurious and based on their mutual connection with managerial characteristics \(\eta_i\). We examine the relevance of this fixed effect in our specification using the Hausman test. The result of this test is that we can estimate specification (1) using random-effect estimations, which are more efficient than fixed-effect estimations.9

Second, the previous estimation may have reverse causality problems: BE value may help firms obtain resources from financial markets that can be devoted to social issues (i.e., slack theory; see McGuire, Sundgren, & Schneeweis, 1988; Waddock & Graves, 1997). We address this endogeneity concern related to reverse causality by using instruments of the potential endogenous variables (the overall CSR score, community, customer, corporate governance, employees, and suppliers). To construct such instruments, we run an estimation of each potential endogenous variable in terms of the following explanatory variables: the corresponding dependent variable lagged by one and two periods, respectively10; Size; ROA; Leverage; and R&D intensity as defined in Table 1. After running such estimations, we compute the predicted value of each estimation.11 Such predicted variables are taken as instruments of the endogenous variables. Note that there are two conditions that a good instrument has to satisfy. First, an instrument should show a high correlation with the instrumented variable, and second, an instrument should show null correlation with the error term in the specification explaining BE. The predicted values computed using the lagged values of the endogenous variables (CSR and different stakeholders’ satisfaction variables) and control variables are, by design, highly correlated with the instrumented variables, given the inertia of a firm’s CSR policy.12 Moreover, we do not expect such instruments to be correlated with the error term in the specification of BE. Note that once we compute the predicted value of each endogenous variable, we are imposing that the error term of the corresponding specification is equal to 0. Thus, we are eliminating the part of the endogenous (CSR and different stakeholders’ satisfaction) variables that is not explained by the lagged dependent variables up to 2 periods or the control variables. This unexplained part is, by design, very likely to be connected to the error term in the specification (1) of BE. The elimination of this error component also allows for the elimination of the correlation between the error term in specification (1) of the BE variable and the instruments (predicted variables). Then, both conditions of an instrument are satisfied.13

Third, we estimate a partial adjustment model (Hanssens, Parsons, & Schultz, 2001) in which we include the dependent variable lagged by one period. The inclusion of this variable enables us to tackle adjustment costs associated with changes in a firm’s brand value. The implicit assumption is that firms approach an optimal level of BE with some adjustment costs. In addition, with this approach, we can compute both long-term and short-term effects.14 One criticism of this model is that the error terms may be correlated over time. We test for this possibility and do find that a first-order correlation exists in the error term. Thus, we conduct a general least squares (GLS) random-effect estimation, specifying both AR(1) autocorrelation and heteroskedasticity in the error term. In the estimations, we cluster the error term at firm level.

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6 For example, the items that are more related to practical issues involving the community are weighted more heavily for public services: transportation, radio, television, electric, gas, and sanitation (SIC = 4) than for manufacturing: tobacco and, beverages (SIC = 2).

7 Investment in R&D improves a firm’s technology capability that, on the one hand, can accommodate better products to consumer preferences and, on the other hand, improve productivity that, in turn, increases financial performance. Both features lead to an increase in a firm’s BE.

8 We assume the same carryover effects for all stakeholders. Our assumption of no differential lags on the impact of the different stakeholders’ satisfaction on BE relies on our theoretical framework in which we posit that all stakeholders have an impact on BE without differentiating temporal lags among them. This assumption is widely used in the literature connecting social performance with financial performance (see the meta-analyses of Margolis & Walsh, 2003; Orlitzky et al., 2003).

9 We also rely on random-effect estimations because of the persistence in the variables related to CSR policies (low intertemporal variability). This persistence makes fixed-effect estimations, which are based on differences over time, particularly inefficient. Additionally, there is high inertia in the dependent variable — BE, which is captured by the high value of the \(\alpha_0\) parameter that measures adjustment costs.

10 We have included up to 2 lagged-period variables in the estimations used for constructing the instruments because of the presence of the dependent variable (BE) lagged by one period as explanatory in specification (1).

11 These predicted values are the result of multiplying the different estimated coefficients by the explanatory variables taken in their mean value of the distribution.

12 The coefficients of the lagged dependent variables in all specifications are larger than 0.6 with p < .01. The variable that shows the greatest persistence is the community, with a coefficient of 0.647. These figures are indicative of the significant correlation between the instruments and the instrumented (CSR) variables.

13 Additionally, and in accordance with the previous two conditions, we have also conducted two tests, which are reported in Table 3, to measure the relevance of the instruments and their exogeneity. First, we show an F-test developed by Stock and Yogo (2005) that measures the explanatory power of the instruments of the endogenous variable. The second is the Hansen test to contrast the overidentification restriction, that is, whether instruments are orthogonal to the error term (Rasche, 2008). All instruments pass the previous tests as shown in Table 3.

14 The partial adjustment model proposed assumes that all dimensions of CSR are short- and long-term determinants of BE. This assumption conforms to our theoretical framework in which our theoretical contents apply to short- and long-term scenarios.
Hypothesis H1 is confirmed when the coefficient of CSR in explaining BE is significantly positive. We test Hypothesis H2 if \( \alpha_1 > 0, \alpha_2 > 0, \alpha_3 > 0, \alpha_4 > 0 \) according to specification (1). Hypothesis H3 is tested if \( \alpha_1, \alpha_5 > \text{Max}(\alpha_6, \alpha_7, \alpha_8) \). Finally, we test Hypothesis H4 with the coefficients \( \alpha_6, \alpha_7, \alpha_8 \) and \( \alpha_9 \) of the terms that result when we cross the variable community with the variables that capture CSR policy with respect to the remaining stakeholders (customer, corporate governance, employees, and suppliers). Hypothesis H4 is confirmed when \( \alpha_6, \alpha_7, \alpha_8 \) and \( \alpha_9 \) are significantly positive and there is a significant improvement in the \( R^2 \) value from the model without interactions.

3.3. Results

3.3.1. Descriptive statistics
Table 2 shows the means, standard deviations, minimum and maximum values, and the correlations of the variables used in the specification (1). The correlation matrix shows that BE is positively correlated with all stakeholders and mainly with community (25%) and customers (20%). This evidence is in line with Hypotheses H1, H2, and H3. However, we cannot extract definitive conclusions from this preliminary analysis given that such a correlation analysis does not control for the possibility of spurious connections related to variables such as Size. In addition, among the control variables, large firms, more profitable firms, and firms that invest in R&D are all positively correlated with BE. Almost all correlations between the explanatory variables are below 0.70, and the variance inflation factors are below 10 except for the term community \( \times \) customer (10.27), indicating that multicollinearity is not a critical problem.

3.3.2. Main effects of CSR
Table 3 shows the results of the model specification (1). Column 1 includes the aggregate score of CSR as an explanatory variable; in column 2, we disaggregate this variable in its different dimensions (community, customer, corporate governance, employees, and suppliers). In both cases, we use the instrumental variables, as we explained in the Methodology section (3.2).

We find that a firm’s CSR has a positive impact on BE (\( \alpha_0 = 0.657, p < 0.01 \)). For the different dimensions of a firm’s CSR (see column 2), we find that community (\( \alpha_1 = 0.725, p < 0.01 \)), customer (\( \alpha_2 = 0.544, p < 0.01 \)), corporate governance (\( \alpha_3 = 0.510, p < 0.01 \)), employees (\( \alpha_4 = 0.491, p < 0.01 \)), and suppliers (\( \alpha_5 = 0.511, p < 0.01 \)) have a positive effect on a firm’s BE value. The above results support Hypotheses H1 and H2.

Community and customer CSR have indeed the largest effects on BE (column 2 of Table 3). However, the t-tests show no significant differences between any of the coefficients compared (all \( p > 0.10 \)).

### Table 2. Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>VIF</th>
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<th>3</th>
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<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
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<tbody>
<tr>
<td>1 Brand equity (BE)</td>
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<td>18172</td>
<td>14900</td>
<td>14740</td>
<td>2490</td>
<td>65174</td>
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<td>2 Customer (%)</td>
<td>243</td>
<td>56.28</td>
<td>22.72</td>
<td>4.50</td>
<td>92.46</td>
<td>5450</td>
<td>24.8</td>
<td>0.20</td>
<td>0.62</td>
<td>1.00</td>
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<td>3 Corporate governance (%)</td>
<td>243</td>
<td>50.39</td>
<td>22.58</td>
<td>4.67</td>
<td>90.48</td>
<td>467</td>
<td>2.48</td>
<td>0.09</td>
<td>0.67</td>
<td>0.70</td>
<td>1.00</td>
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<td>4 Employee (%)</td>
<td>243</td>
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<td>19.35</td>
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<tr>
<td>5 Community × Suppliers</td>
<td>243</td>
<td>1879.65</td>
<td>1669.96</td>
<td>0.00</td>
<td>7125.00</td>
<td>6.59</td>
<td>0.10</td>
<td>0.70</td>
<td>0.52</td>
<td>0.48</td>
<td>0.79</td>
<td>0.45</td>
<td>0.57</td>
<td>0.67</td>
<td>0.65</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 Size</td>
<td>243</td>
<td>16.51</td>
<td>4.43</td>
<td>10.33</td>
<td>26.35</td>
<td>256</td>
<td>1.32</td>
<td>0.10</td>
<td>0.18</td>
<td>0.04</td>
<td>0.04</td>
<td>0.07</td>
<td>0.09</td>
<td>0.09</td>
<td>0.13</td>
<td>0.10</td>
<td>0.10</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td>7 Innovation</td>
<td>243</td>
<td>0.33</td>
<td>2.76</td>
<td>0.00</td>
<td>4.22</td>
<td>2.44</td>
<td>0.05</td>
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<td>0.09</td>
<td>0.37</td>
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<td>0.13</td>
<td>0.08</td>
<td>0.32</td>
<td>0.15</td>
<td>0.04</td>
<td>0.08</td>
<td>0.05</td>
<td>0.03</td>
</tr>
</tbody>
</table>

**Note:**
- We have denoted the figures for Brand equity (BE) on a normal scale (million US $) to provide a clear picture of the magnitude of brand value of the firms in our sample. However, to be consistent with the specifications estimated, we provide VIF as well as correlations using BE on a log scale.

---

15 The coefficients that capture the long-term effects are \( m_{11}, m_{12}, m_{13}, m_{14}, m_{15}, m_{16} \).

16 Four correlations involving interaction terms are slightly above the threshold of 0.70; to test whether this feature generates serious multicollinearity problems, we have re-estimated the complete specification using a dummy \( D_{\text{Community}} \) instead of the continuous variable community. The previous dummy is equal to 1 (0) when community is above (below) the mean value for the corresponding sector and year. The interaction terms with the dummy show correlations below 0.70; hence, multicollinearity is less problematic. Remarkably, the results using such alternative interaction terms are similar to those shown in Table 3.

17 Consistent with the lack of multicollinearity problems, we have conducted the Belsley (1991) test, which establishes that a condition number above 30 is a signal of multicollinearity problems. In our case, the condition number for the full specification model of column 3 in Table 3 (instruction condition in STATA) is 23.7. Additionally, we conducted different estimations that include single interaction terms that cross Community times the different stakeholders. We compared the results with those of the complete specification of column 3 in Table 3, which includes all of the interaction terms (available upon request). The coefficients found in the different specifications are quite stable, which is indicative of the lack of serious multicollinearity problems.
values > .10.18 Hence, we find no significant empirical support for Hypothesis H3.

Among the control variables, large firms that are more visible (α_{10} = 0.060 with \( p < 0.01 \)) or more profitable (α_{1} = 0.032 with \( p < 0.10 \)), and firms that invest in R&D (α_{3} = 0.095 with \( p < 0.05 \)), which creates intangible assets, have higher BE values.

Finally, the inclusion of the lagged term of BE in our model allows for the assessment of the long-term effects of CSR activities. The significant coefficient of Brand Equity_{t−1} in column 2 of Table 3 (α_{6} = 0.910, \( p < 0.01 \)) indicates that all stakeholders are significant determinants of long-term BE value. In particular, (\( \frac{\alpha_{2}}{1-\alpha_{6}} = 8.055 \) with \( p < 0.01 \)) for community; (\( \frac{\alpha_{2}}{1-\alpha_{6}} = 6.044 \) with \( p < 0.01 \)) for customer; (\( \frac{\alpha_{2}}{1-\alpha_{6}} = 5.667 \) with \( p < 0.01 \)) for corporate governance; (\( \frac{\alpha_{5}}{1-\alpha_{6}} = 5.455 \) with \( p < 0.01 \)) for employees; and (\( \frac{\alpha_{5}}{1-\alpha_{6}} = 5.678 \) with \( p < 0.01 \)) for suppliers.

3.3.3. Interaction effects with CSR community

Column 3 of Table 3 shows the tests of Hypothesis H4 and includes four alternative interaction terms (community × customers, community × corporate governance, community × employees, and community × suppliers). These variables test the possible moderating effect of community and the different stakeholders on BE.

In accordance with column 2, all stakeholders have positive impacts on a firm’s BE. Regarding the interactive terms, we find that community, interacting with the remaining stakeholders’ variables, enhances the positive impact of these latter variables on BE. In particular, community positively moderates the effect of customer on BE (\( \alpha_{1} = 0.004 \) with \( p < 0.01 \)). Hence, although we do not find larger effects of CSR toward community and toward customers than we do with other stakeholders, we do find that the combination of CSR toward community and customers generates larger effects on BE than other stakeholders do individually.19 By the same token, community plays a positive moderating role in the connection of shareholder value (corporate governance) to BE value (\( \alpha_{7} = 0.002 \) with \( p < 0.05 \)). These results also hold for employees (\( \alpha_{6} = 0.0015 \) with \( p < 0.05 \)) and suppliers (\( \alpha_{7} = 0.0019 \) with \( p < 10.10 \)). Remarkably, the moderating effect of community is larger when combined with CSR toward customers than when combined with other stakeholders.20 This result confirms our statement that the effects of credible CSR policies (i.e., CSR toward community) will have particularly large effects when combined with visible CSR policies such as those of CSR toward customers.

Finally, the coefficient of the dependent variable lagged by one period is still significant at \( p < 0.01 \), and thus, we can state that the previous moderating results also hold for the long-term analysis. All of these results confirm Hypothesis H4.

Concerning the model fit, the \( R^2 \) value is very high (98.97%), and this result is an improvement on the model of column 2 (\( \Delta R^2 = 3.04, p = 0.034 \)), which indicates that community plays a significant moderating role in the model of column 3.21 Remarkably, once we extract the lagged dependent variable from the specification, the \( R^2 \) value decreases to 49.72%. Approximately one half of the explanatory power is due to the lagged dependent variable. This result is evidence that there is considerable inertia in BE, indicating that CSR investment has long-lasting effects on BE value.

4. Discussion, implications, limitations and future research

4.1. Discussion of results

In this paper, we analyze the effect of different dimensions of a firm’s corporate social responsible (CSR) policy on the creation of global brand equity (BE). Studying CSR for global brands is highly relevant, as global brands are frequently blamed for not having strong CSR records. Our study, using a longitudinal database of 57 global brands in various industries and 10 different countries, shows the strong effects of CSR initiatives directed at different stakeholders on global BE. Below, we discuss our most important results and reflect on the implications for the management of global brands.

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18 We are using the \( \sqrt{\frac{\alpha_{2} - \alpha_{1}}{\alpha_{2} - \alpha_{1}}} \) statistic to test significant differences between the coefficients of community and customers (\( \alpha_{2} \) and \( \alpha_{3} \)) and those of corporate governance, employees and suppliers (\( \alpha_{4} \) and \( \alpha_{5} \)).

19 In the specification of column 3, we will also see that community × customers generates larger effects not only to other individual stakeholders but also to the combination of these latter stakeholders to community.

20 When we compare the coefficient of community × customer to community × corporate governance, the t-test of differences shows a p-value = 0.025. The p-value is 0.020 for the comparison between community × customer and community × employees. Finally, the comparison between community × customer and community × suppliers leads to a t-test p-value = 0.059.

21 Such a high \( R^2 \) value is similar to other studies that include the lagged dependent variable as an explanatory factor. For example, Sriram, Balachander, and Kalwani (2007) found an \( R^2 \) of 92% explaining BE by that variable lagged by one period and advertising innovation and sales promotion variables.
First, we find that CSR positively affects global BE. This result is an important extension of the previous literature on CSR, as it is the first study to actually show this effect in an international setting. This result confirms prior studies showing that CSR affects firm performance (e.g., Luo & Bhattacharya, 2006; Margolis & Walsh, 2003; Orlitzky et al., 2003). Moreover, we also show that CSR directed at stakeholders generates a positive effect on both short-term and long-term BE values.

Second, CSR toward community and toward customers does not have a significantly larger effect on a firm’s global BE than the other CSR efforts. However, the combination of both CSR policies (toward customers and toward community) does have a larger impact on BE than CSR toward other stakeholders. These results do not confirm that CSR initiatives that are more visible or credible in the marketplace have a greater effect on BE. Nevertheless, they do confirm that joint CSR initiatives combining visibility (customers) and credibility (community) have a stronger effect on a marketing metric such as global BE than other combinations. This result confirms claims made by Wood and Jones (1995) that there should be a match between the CSR initiative and the outcome measure. The insignificance of the differences of our findings on the direct effects for the different stakeholders can potentially be attributed to the relatively small number of firms in our sample. Beyond that, we may argue that “internal” stakeholders such as employees and suppliers are as important as community and customers, given that they provide the type of valuable, intangible resources that are the basis of a firm’s competitive advantage, which, in turn, enhance a firm’s BE. Another explanation might be that, as already noted, CSR visibility can also have some negative effects, as it may cause a stronger salience of the firm’s self-benefitting motives for CSR (Yoon et al., 2006).

These possible negative effects are why it is particularly important to combine visible CSR (directed at customers) with credible CSR (directed at community).

Third, the importance of CSR toward communities is emphasized by the interaction effects that have been found with CSR toward community and CSR initiatives toward other stakeholders and particularly toward customers. These results point to the indirect beneficial effect of CSR toward community. The satisfaction of community interests gives credibility to a firm as an entity with an ethical stance to all stakeholders (Godfrey et al., 2009). Gaining such a reputation has its own direct value, particularly to global brands. In the event of shock-generating controversies in parts of the organization, a gained reputation in social issues may prevent the growth of a negative image throughout the organization, which could seriously damage a global brand image. The indirect effect of CSR toward community is a reinforcing mechanism (positive moderator), in terms of its positive impact on BE in satisfying all stakeholders’ interests. Such a reinforcing mechanism reflects the trust that arises from firms applying credible CSR practices toward secondary stakeholders (Logsdon & Wood, 2002). Furthermore, connections to distant stakeholders are more informative than connections to closer stakeholders in assessing a firm’s credibility on its ethical stance (Granovetter, 1983). Therefore, a global brand that has gained trust through its relationship with community will be capable of lending confidence to all its stakeholders regarding its long-term commitment, which in turn will have a positive effect on its short-term and long-term BE values. Finally, we argue that for the large and complex organizations that are behind global brands, information asymmetries and the need for monitoring are particularly important (Zajac & Westphal, 1994). In this framework, the implementation of credible CSR policies such as those targeted toward community will reduce opportunistic behaviors that emerge in information asymmetry contexts. The result is a creation of brand value.

4.2. Managerial implications

Our findings provide several implications for managers.

First, we demonstrate that global brand managers should indeed incorporate CSR as a primary component of their brand equity-enhancing strategy, as Polonsky and Jevons (2009) suggest. Second, managers who wish to send visible and credible signals of commitment to enhance their firms’ global BE value should pay particular attention to the less salient stakeholders. That is, global brand management should give substantial weight to satisfying local community interests. To illustrate the importance of focusing on CSR for global brands and specifically the strong effects of CSR toward community, we have performed an analysis of the economic consequences of improving different CSR components. In economic terms, when we do not consider interaction effects, the marginal impact of CSR toward customer on BE is given by the coefficient (α2 = 0.518, p < 0.01). However, when we consider interaction effects with community, once we fix CSR toward community at its mean value of the distribution (58.16), the marginal effect of CSR toward customers on BE is given by the coefficient (α2 + α6 × Mean(Community) = 0.518 + 0.004 × 58.16 = 0.751, p < 0.01). These coefficients indicate that an increase in one standard deviation in customer satisfaction (0.227) leads to an increase in $1752.24 million in BE,22 or an 11.76% increase from the mean value of BE ($14,900 million), without considering interaction effects. This figure increases to 17.04% ($2538.96 million) when we include the moderation of community, which means that the moderating effect of community is translated to a relative increase of 44.90% ($786.72 million) in BE value. When we apply the same type of analysis to corporate governance, the numbers are a 9.57% increase when we do not consider interaction effects and a 12.20% increase ($1817.8 million) when we consider interaction effects and fix community at its mean value. For employees, the increase is 8.09% when we do not consider interaction effects and 9.78% ($1457.22 million) when we consider interaction effects. Finally, for suppliers, the figures are 9.84% and 12.46% ($1856.54 million), respectively. Thus, the variations in the different CSR dimensions lead to considerable economic variations in BE and particularly when community moderates CSR toward customers.

Therefore, global brands that aim to improve their BE with CSR should develop CSR initiatives toward communities that reinforce CSR initiatives with other stakeholders. CSR initiatives toward the local community can be especially valuable, as they may integrate with existing global brand strategies. Specifically, firms can pursue a dual strategy of creating a global brand and developing symbols at a local level (Alden et al., 2006) through the satisfaction of local community interests. This type of strategy is followed by firms such as Coca-Cola and Heineken, which are perceived simultaneously as global brands and as firms with strong roots in different national communities (Alden et al., 2006).

Third, the relevance of CSR for global brands also has implications for their merger and acquisition strategies. Global brands that expand internationally and wish to create certain standards of CSR policies abroad should acquire firms with strong community roots. In short, global brand managers need to be aware that local satisfaction is at the root of improving global BE value. Such a strategy would eliminate fears of corporate expropriation by entrant firms in less developed countries.

Lastly, one final implication is that managers should not focus on single-stakeholder CSR policies, particularly managers of global brands. These multinational enterprises (MNEs) should be particularly conscious of maintaining a balance among different stakeholders in the generation of BE. Managers of global brands should not put excessive weight on market-oriented stakeholder-like customers. Brands are complex social phenomena, and thus, managers who wish to sustain CSR policies that create global BE value should maintain a balance...
among the different stakeholders rather than focus on a single stakeholder (Maio, 2003). That is, all components of CSR have a positive impact on global brands.

4.3. Limitations and future research avenues

One of the limitations of our study is that the MNEs analyzed are based in developed countries, which may question the generalizability of the results. Moreover, the use of the Interbrand measure, which focuses on strong (global) brands, strengthens this problem. However, the measurement approach of Interbrand, which is not based on customer surveys but on proprietary information, may open the possibility of extracting information from subsidiaries of MNEs operating in less developed countries. Nevertheless, we may speculate that the effect of establishing socially responsible policies in developing countries is a powerful signal of MNE commitment to stakeholders, and we may expect that the effect on BE should be even clearer in developed countries. Further research should be extended to developing countries and emerging economies, e.g., Turkey, Brazil, and China (Burgess & Steenkamp, 2005). A second limitation is the dichotomous items used in the definition of the proxies on social responsibility to the different stakeholders. We have minimized this problem by averaging a broad set of items to obtain a continuous-type variable.

Our findings reveal that satisfying community interests is highly relevant to creating and maintaining global brand value. A natural extension of our model would be to incorporate virtual communities into the analysis to determine whether the reinforcing effects linked to real communities also hold for these types of communities. Another avenue would be to include other stakeholders in the analysis. For example, research could assess whether the crucial role of CSR toward one secondary stakeholder (community) differs from that toward other secondary stakeholders, such as the environment. The absence of environment-related CSR in our measurement of CSR is a limitation. Hills and Welford (2005) discuss the relevance of the environmental issue for Coca-Cola, suggesting the potential relevance of this CSR issue in a global branding context. This relevance is confirmed indirectly in our analysis, given that some items in community score refer to environmental issues. Finally, a contingency analysis of the economic cycle would be of interest. Following existing research on the consequences of the economic cycle (e.g., Lamey, Deleersnyder, Dekimpe, & Steenkamp, 2007), it is of crucial importance to understand whether and which CSR policies become more or less relevant during economic recessions. Moreover, it would also be relevant to investigate whether the global BE of brands that have invested in CSR is less affected by, or may even benefit from, strong market crises such as the recent financial crisis. Initial case-based evidence in the Dutch banking market suggests that the cooperative Rabobank, which has clear local community CSR initiatives, has been less affected by the global crisis (Verhoef, Wesselsius, Bügel, & Wiesel, 2010). Future research could investigate this issue empirically.

Acknowledgments

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Appendix A. Corporate sustainability rating

<table>
<thead>
<tr>
<th>Stakeholder (j)</th>
<th>Items (i)</th>
<th>Score (%)</th>
<th>Weight $W_i$</th>
<th>Weighted score (%)</th>
<th>Weight $W_i$</th>
<th>Weighted score (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Community</td>
<td>Local communities’ programs</td>
<td>100</td>
<td>0.014</td>
<td>1.379</td>
<td>0.154</td>
<td>15.385</td>
</tr>
<tr>
<td></td>
<td>Formal policy on local community involvement</td>
<td>100</td>
<td>0.021</td>
<td>2.069</td>
<td>0.231</td>
<td>23.077</td>
</tr>
<tr>
<td></td>
<td>Management responsibility for local community affairs</td>
<td>100</td>
<td>0.014</td>
<td>1.379</td>
<td>0.154</td>
<td>15.385</td>
</tr>
<tr>
<td></td>
<td>Formal volunteer programs</td>
<td>0</td>
<td>0.014</td>
<td>0.000</td>
<td>0.154</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Programs for consultation with local communities</td>
<td>0</td>
<td>0.014</td>
<td>0.000</td>
<td>0.154</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Percentage of donations directed at local communities</td>
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<td>0.014</td>
<td>0.276</td>
<td>0.154</td>
<td>0.007</td>
</tr>
<tr>
<td>Customer</td>
<td>A formal policy statement noting customer issues</td>
<td>100</td>
<td>0.010</td>
<td>1.034</td>
<td>0.083</td>
<td>3.797</td>
</tr>
<tr>
<td></td>
<td>Formal policy on product quality</td>
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<td>5.172</td>
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</tr>
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<td>Formal policy on marketing/advertising practices</td>
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<td>0.028</td>
<td>2.759</td>
<td>0.101</td>
<td>10.127</td>
</tr>
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<td></td>
<td>Facilities with quality certification</td>
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<td>Marketing practices to satisfy customers</td>
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<td>0.000</td>
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<td>Customers score</td>
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<td>“One share, one vote” principle</td>
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<td>0.096</td>
<td>9.615</td>
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<tr>
<td></td>
<td>Abse::ce of anti-takeover devices</td>
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<td>0.017</td>
<td>0.000</td>
<td>0.096</td>
<td>0.000</td>
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<tr>
<td>Corporate governance</td>
<td>Number of board committees</td>
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<td>0.010</td>
<td>0.621</td>
<td>0.058</td>
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<td>Managerial stock ownership (%)</td>
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<td>0.138</td>
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<tr>
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<td>The company has corporate governance principles</td>
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<td>34.615</td>
</tr>
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<td></td>
<td>Directors’ terms of office</td>
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<td>0.038</td>
<td>0.769</td>
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<td></td>
<td>Board performance evaluation</td>
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<td>0.038</td>
<td>0.000</td>
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<td></td>
<td>Number of NEDs in the Board</td>
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<td>1.724</td>
<td>0.096</td>
<td>9.615</td>
</tr>
<tr>
<td></td>
<td>Separate position for chairman of board and CEO</td>
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<td>0.017</td>
<td>1.724</td>
<td>0.096</td>
<td>9.615</td>
</tr>
<tr>
<td>Employees</td>
<td>Policies/principles regarding employees</td>
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<td>0.042</td>
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<td>Formal policy statement on health and safety</td>
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<td>9.722</td>
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<tr>
<td></td>
<td>Formal policy on diversity/employment equity</td>
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<td>0.024</td>
<td>2.414</td>
<td>0.097</td>
<td>9.722</td>
</tr>
<tr>
<td></td>
<td>Formal policy on freedom of association</td>
<td>100</td>
<td>0.024</td>
<td>2.414</td>
<td>0.097</td>
<td>9.722</td>
</tr>
<tr>
<td></td>
<td>Formal policy statement on child/forced labor</td>
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<td>0.010</td>
<td>1.034</td>
<td>0.042</td>
<td>4.167</td>
</tr>
<tr>
<td></td>
<td>Formal policy statement on working hours</td>
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<td>0.024</td>
<td>2.414</td>
<td>0.097</td>
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</tr>
<tr>
<td></td>
<td>Formal policy statement on wages</td>
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<td>0.010</td>
<td>1.034</td>
<td>0.042</td>
<td>4.167</td>
</tr>
</tbody>
</table>
Appendix A (continued)

<table>
<thead>
<tr>
<th>Stakeholder (j)</th>
<th>Items (i)</th>
<th>Score (%)</th>
<th>Weight</th>
<th>Weighted score (%)</th>
<th>Weight</th>
<th>Weighted score (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$s_{ij}$</td>
<td>$w_i$</td>
<td>$s_{ij} \times w_i$</td>
<td>$w_i$</td>
<td>$w_i \times S_j$</td>
</tr>
<tr>
<td>8</td>
<td>Board responsibility for human resources</td>
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<td>0.017</td>
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<td>Specific health and safety targets</td>
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<td>10</td>
<td>Diversity/equal opportunity programs</td>
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</tr>
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<td>11</td>
<td>Work/life programs</td>
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<td>Training programs</td>
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<td>0.000</td>
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<td>0.000</td>
</tr>
<tr>
<td>14</td>
<td>Cash profit-sharing programs</td>
<td>0</td>
<td>0.010</td>
<td>0.000</td>
<td>0.042</td>
<td>0.000</td>
</tr>
<tr>
<td>15</td>
<td>Supervisory Board (NEDs)</td>
<td>100</td>
<td>0.007</td>
<td>0.069</td>
<td>0.028</td>
<td>2.778</td>
</tr>
</tbody>
</table>

Supports sustainability provides a wide range of research and consultancy services to the largest asset managers, insurance companies, pension funds, banks, and social investment institutions in the world. One of these services is the Sustainalytics Global Profile (SGP). SGP provides a rating that enables users to integrate firms’ detailed profiles in a unique rating that contains 199 information items. These information items are translated into a more comprehensive format—a rating—by implementing Likert-type scales and then, they are grouped into eight research sections. The first provides a description of ethical/unethical corporate activities such as political donations, corruption and bribery, and the existence of business ethics programs addressing these issues. The last section measures the degree of involvement in controversial business activities such as those involving gambling, alcohol, pornography, animal testing, and tobacco. The realization of one of these controversial activities is motive of exclusion of the SGP sustainability index. The remaining six sections cover different issues of the six stakeholders analyzed (community; customers; employees; corporate governance; suppliers and environment). In particular, for each stakeholder, the database addresses the level of a firm’s involvement in four different areas: the level of a firm’s transparency/disclosure, the existence of corporate policies and principles for the stakeholder, the importance of management procedures, and the level of controversies in the relationship with this stakeholder. In each of these areas, there are different information items that give a score using a Likert-type scale. Also, each information item has a weight according to a methodology developed by the SGP. The final score provided by the SGP is the sum of each of the scores of all the items averaged by its corresponding weight. Also, the database gives scores for each stakeholder. These scores are computed through the weighted average of the corresponding information items to a given stakeholder normalized by the sum of the weights of the items for the corresponding stakeholder. For clarification purposes, below, we describe in detail the information items that we consider in the paper for a specific real company (Nestle). In particular, we focus on those items related to policies, principles, and managerial procedures of the five stakeholders that are considered in the study (community, customers, corporate governance, employees, and suppliers).


References


Why consumers do (not) like global brands: The role of globalization attitude, GCO and global brand origin

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“At the consumer level, there are mixed views amongst society at large as to whether globalization operates for good or evil” (Paliwoda & Slater, 2009, p. 375).

1. Introduction

Since the early 1980s, marketing literature has highlighted the homogenization of consumer needs and desires across the globe (Levitt, 1983) and suggested that companies might address this homogenization with a standardized global product or service (Keillor, D’Amico, & Horton, 2001). In recent decades, many multinational companies have followed this suggestion and altered their brand portfolios in favor of global brands (e.g., Schulling & Kapferer, 2004). Corporations are motivated to launch global brands to (a) explore economy of scale effects in R&D, manufacturing, and marketing (Yip, 1995); (b) accelerate time to market for innovations (Neff, 1999); and (c) create a global image (Kapferer, 1997). Initially, the literature assumed that brand globality created perceptions of quality and prestige that were attractive to all consumers (e.g., Alden, Steenkamp, & Batra, 1999; Johansson & Ronkainen, 2005; Steenkamp, Batra, & Alden, 2003). However, more recent studies suggest that 20% of US consumers are against globalization (Dimofte, Johansson, & Ronkainen, 2008) and that 10% of consumers worldwide avoid global brands if local alternatives are offered (Holt, Quelch, & Taylor, 2004). Consequently, an increasing number of critical voices have challenged the assumption of exclusively positive global brand associations (e.g., De Mooij, 1998; Holt et al., 2004).

Global consumption orientation (GCO) differentiates consumer groups favoring global brands from those favoring local brands (Alden, Steenkamp, & Batra, 2006; Steenkamp & de Jong, 2010). Insights into why consumers differ in their attitudes towards global brands are scant (Özsomer & Altaras, 2008; Steenkamp et al., 2003). One potentially relevant factor might be consumers’ globalization attitude (GA) because global brands can be associated with either the benefits or drawbacks of globalization. Global brands, such as Coca Cola, McDonald’s, or Nike, can be seen either as icons of a globalized lifestyle or as symbols of cultural homogenization that threaten local competition (Ritzer, 2004; Thompson & Arsel, 2004). As visible symbols of globalization, these brands have become popular targets of anti-globalization protests (Holt et al., 2004). Initial empirical evidence of an attitude transfer between consumers’ GA and their attitudes towards global brands has only recently emerged (Dimofte et al., 2008). Dimofte et al. (2008), however, used an ad-hoc measure for GA, which referred to global brands in generic terms, and they did not test any underlying theoretical model.

Assuming that consumers favor globalization, global brand managers frequently try to position their brands as global (Alden et al., 1999) while disguising the brand’s geographical origin. Despite these attempts to disguise brand origin, which has in general become difficult to correctly identify due to cross-national sourcing, production, assembly, etc. (Balabanis & Diamantopoulos, 2008; Samiee, Shimp, & Sharma, 2005), consumers still have a perception of whether brands are domestic or non-domestic. Although most studies of global brands are based on cross-national samples (e.g., Alden et al., 2006; Steenkamp & de Jong, 2010; Steenkamp et al., 2003; Strizhakova, Coulter, & Price, 2008), these studies do not consider brand origin. For example, attitudes towards Coca Cola were tested in the same manner for US consumers, for whom the brand is domestic, as for Korean consumers, for whom the brand is non-domestic. We extend categorization theory to global brand literature and propose that both brand globalization and brand origin are relevant for global brand studies.

Against this background, the present article aims to advance global brand knowledge by (1) estimating the influence of GA and GCO for a set of real global brands using a belief-attitude-behavior model (Ajzen & Fishbein, 1980), and (2) investigating the moderating effect of perceived domestic/foreign brand origin on these relationships. From a managerial perspective, the present study demonstrates that GA plays a decisive role in consumers’ stance towards global brands and that perceived brand origin does matter for global brands.

2. Conceptual background and theoretical model

2.1. Categorization of domestic versus foreign global brands

Consumers categorize brands according to their associated origins, i.e., the countries in which they, correctly or erroneously, believe that
a brand originates from (Balabanis & Diamantopoulos, 2011). Using categorization theory (e.g., Ratneswar, Barsalou, Pechmann, & Moore, 2001; Smith, 1995), Balabanis and Diamantopoulos (2011) showed that consumers’ categorization of brands to different countries of origin (COOs) affects their inferences regarding brand attributes and their associated behavioral intentions. We extend this theory to global brand literature and propose that consumers engage in a dual categorization with regard to (a) brand origin and (b) brand globality. Perceived brand origin refers to the country of association (Josiassen & Harzing, 2008), while perceived brand globality refers to a brand’s geographical awareness and reach (Özsomer & Altaras, 2008).

Based on the COO literature, a COO categorization might be made by reference to a particular country of association (Josiassen & Harzing, 2008), or by applying a dichotomy of domestic versus non-domestic (Balabanis & Diamantopoulos, 2004). The first approach thus considers the effects of specific countries (such as country image, product country image, developing versus developed COO), whereas the second approach reduces complexity and captures a possible “home country bias”. The latter phenomenon reflects a result of affective brand processing whereby domestic products are evaluated more positively than products from other COOs irrespective of objective quality (Balabanis & Diamantopoulos, 2004, 2011).

In this paper, we adopt the second approach of COO categorization and apply a domestic versus non-domestic dichotomy. Domestic and non-domestic (foreign) brand origins are defined in terms of consumer perceptions. This approach minimizes the problem of incorrect categorization or inability to categorize the COO (Balabanis & Diamantopoulos, 2008, 2011; Samiee et al, 2005), which might be particularly prevalent among global brands.

2.2. Focal constructs: Delineating GA and GCO

Globalization refers to the “process of reducing barriers between countries and encouraging closer economic, political, and personal interaction” (Spears, Parker, & McDonald, 2004, p. 57). Economic globalization includes the free movement of capital, products, and labor. Because consumers take various stances towards economic globalization, from a consumer perspective, globalization is “mostly a state of mind” (Friesen, 2003, p. 22). Studies show that worldwide GA among individuals is divided (Leiserowitz, Kates, & Parris, 2006), ranging from pro-globalization to anti-globalization (Dimofte et al, 2008). Because global companies play a pivotal role in the globalization process, individual reactions to the globalization process are directed mostly towards these companies and their products (Das, 2007).

According to consumer culture theory, individuals in today’s post-modern world define and orient their core identities in relation to consumption (Holt, 2002). At the same time, consumers experience a mélange of local culture(s) and globalization influences that renders localism and globalism the “two axial principles of our age” (Tomlinson, 1999, p. 90). In this context, the concept of GCO describes a set of “attitudinal responses to the global diffusion on consumption choices” (Alden et al, 2006, p. 228). Specifically, it distinguishes the following four attitudinal responses to global brands: (1) a conscious opt for global alternatives (i.e., homogenization), (2) an avoidance of global brands in favor of local alternatives (i.e., localization), (3) a combined approach of purchasing both local and global brands (i.e., glocialization; see also Kjeldgaard & Askegaard, 2006), or (4) a lack of interest in the cultural themes of products (i.e., alienation). Homogenization indicates a positive GCO, while localization connotes a negative GCO (Alden et al, 2006).

Although both GA and GCO are attitudinal in nature, they have distinct conceptual domains. GA reflects consumers’ general stance towards the overall process of economic integration, including free movement of labor, capital, and products, and thus assesses an economic–political mentality. GCO, in contrast, is a consumption-domain construct that specifically reflects responses to the availability of global products and services. GCO thus captures a market-based ideology that represents a choice among the plurality of social identities in a post-modern consumer culture (Kjeldgaard & Askegaard, 2006).

The empirical sections of the present paper will provide discriminant validity of these constructs. In theoretical terms, a positive relationship between the two conceptually distinct constructs is to be expected, as an economic–political standpoint and a consumer identity choice will not be independent. Consumers with more positive (negative) GA will have a more positive (negative) GCO.

2.3. Outcome variables: belief–attitude–behavior model

Global brand literature has been criticized for including either brand attitude (e.g., Alden et al, 2006) or purchase intention (e.g., Steenkamp et al, 2003). The present paper proposes a model that intends to overcome this criticism of incomprehensiveness (Özsomer & Altaras, 2008) by including a hierarchy of three outcome variables based on Ajzen and Fishbein’s (1980) belief–attitude–behavior model; namely, global brand evaluation, global brand attitude, and purchase intention. This hierarchy is based on the functional theory of consumer attitude formation, which assumes that cognitive processing of product attributes precedes attitude formation. In particular, Ajzen and Fishbein’s (1980) deliberate attitude model implies that attitudes are formed from cognitive beliefs that are stored in explicit memory (Argyriou & Melewar, 2011). Cognitive beliefs refer to the evaluation of salient brand attributes, while attitudes as a construct represent “a summary evaluation of a psychological object captured in such attribute dimensions as good–bad, harmful–beneficial, pleasant–unpleasant, and likeable–dislikeable” (Ajzen, 2001, p. 29). The latter is viewed as mediator between cognitive beliefs and subsequent behavioral intentions (Fishbein & Ajzen, 1975; Fishbein & Middlestadt, 1997). In line with Ajzen and Fishbein’s (1980) model, positive relationships from brand evaluation to brand attitude as well as from brand attitude to purchase intention are expected (see also Dimofte, Johansson, & Bagozzi, 2010).

2.4. Model and hypotheses

Fig. 1 depicts the proposed theoretical model, which is comprised of (a) GA and GCO as focal constructs, (b) a hierarchy of brand-related outcome variables, and (c) brand familiarity and perceived globality as covariates. The former covariate is known to influence brand perceptions, attitudes and purchase intention (e.g., Keller, 1998), while the latter has been shown to influence brand evaluations (e.g., Steenkamp et al, 2003). Brand origin will be modeled as a moderator for the proposed relationships.

2.4.1. Main effects

Early literature on global brands assumed an unconditional positive effect of brand globality on perceived quality (e.g., Holt et al, 2004; Steenkamp et al, 2003). Recent literature has challenged this perspective by suggesting that this positive halo-effect might be contingent on consumers’ attitudes towards globalization (Dimofte et al, 2008). In this view, the halo-effect would only take place for pro-globalization consumers. In an experimental setting, Zhang and Khare (2009) demonstrate that an accessible global (local) identity, relative to a local (global) identity, induces more positive evaluations of global (local) products. Accordingly, it is expected that the evaluation of global brands is influenced by GA, which in turn implies that consumers who hold positive attitudes about globalization evaluate global brands more positively than others. Hence, we expect a direct effect as follows:

H1. GA is positively related to global brand evaluation.

For the GCO construct, the extant literature fails to provide any empirical studies about its impact on global brand evaluation. From a
theoretical standpoint, the appreciation of global consumption styles is, aside from associations with dreams, success and global citizenship, also built upon the utilitarian convenience of global brands (Alden et al., 1999). This utilitarian convenience largely refers to a simplification of the purchase decision process, as consumers in favor of globality use the latter as a quality signal (Holt et al., 2004; Hsieh, 2002). Coding a brand as global economizes cognitive processing because the stimulus (i.e., the global brand) is evaluated based upon its feature of being global (Keller, 2003; Smith, 1995). Related to the above arguments, we thus expect that a strong GCO results in a more favorable brand evaluation.

**H2.** GCO is positively related to global brand evaluation.

### 2.4.2. Mediated effects

We expect that GA and GCO will have indirect effects on the subsequent outcome variables, i.e., on global brand attitude and purchase intentions. According to the hierarchy-of-effects model, global brand evaluation positively relates to global brand attitude, which in turn positively relates to purchase intention. Consequently, we expect (a) that global brand evaluation mediates a positive relationship between the focal constructs and global brand attitude and (b) that the positive relationship between the focal constructs and purchase intention is subject to a double mediation by global brand evaluation and global brand attitude:

**H3a.** Global brand evaluation mediates the relationship between GA and global brand attitude.

**H3b.** Global brand evaluation mediates the relationship between GCO and global brand attitude.

**H4a.** Global brand evaluation and global brand attitude mediate the relationship between GA and purchase intentions.

**H4b.** Global brand evaluation and global brand attitude mediate the relationship between GCO and purchase intentions.

### 2.4.3. Rival models: additional direct effects

In addition to the hypothesized mediated effects, direct relationships of GA and GCO to global brand attitude and purchase intention appear theoretically plausible and will be tested in two rival models. First, based on Dimoff et al.’s (2008) finding of more favorable attitudes toward global brands in general among pro-globals than among anti-globals, a direct attitude transfer from consumers’ GA to consumers’ attitude towards specific global brands is plausible. Hence, a direct effect of GA on global brand attitude will be included in Rival Model A.

With regard to purchase intentions, the literature discusses the boycott of global brands by anti-globals (e.g., Holt et al., 2004). Given that global brands symbolize economic globalization, they represent manifest vehicles for taking a stance in the globalization debate. Consequently, a positive direct effect from GA to purchase intention is plausible and thus also included in Rival Model A.

According to identity consistency theory, global products should appeal to consumers holding global identities because global brand positioning and self-identity are congruent for these consumers (Zhang & Khare, 2009). The aspirational values of the imagined global community to which these consumers wish to belong (Mato, 2003) are reflected by global brands, and thus a positive attitudinal response to specific global brands might be expected. Empirically, Alden et al. (2006) found a positive relationship between GCO and global brand attitude. To validate this finding and to be comprehensive in our model, we test this direct effect between GCO and global brand attitude in Rival Model B.

Finally, given the positive attitude towards global consumption generally and the perceived benefits of global brands to consumers with positive GCO, it might be expected that consumers scoring higher on GCO are also more inclined to purchase specific global brands. In contrast, consumers with more negative stances towards GCO should avoid the purchase of brands that symbolize globality. Based on these arguments, we also include a direct effect between GCO and purchase intentions in Rival Model B.

### 3. Study I: Testing the model using Red Bull (domestic) & Coca Cola (foreign)

#### 3.1. Data collection

A survey-based design was used for investigating the model presented in Fig. 1. Austria was selected as the research setting because the country ranks second in the KOF globalization index worldwide (http://globalization.kof.ethz.ch/) but, at the same time, is among the most critical of economic globalization (News, 2007). Hence, a wide variation in globalization attitudes among consumers was expected. With regard to the global brands used for testing the model, soft drinks were chosen as a low involvement and hedonic product category. Soft drinks are a typical FMCG product category with many global companies.

For data collection, an area sampling procedure (e.g., Lohr, 1999) of postal code areas was applied with quotas for age and residential area (i.e., metropolitan vs. rural). A total of 5,900 households were targeted, and 442 returned completed questionnaires, resulting in a response rate of 7.5%. This number is not surprisingly low as (a) response rates in postal surveys are commonly low (for comparison, see
Dillon, Madden, & Firtle, 1994; or Steenkamp et al., 2003) and (b) no monetary incentive was offered. After excluding questionnaires with missing values, the sample used for analysis comprised 429 consumers. Of these, 58% were females, the average age was 46.6 years (range: 13 to 93 years), and 60% lived in a rural area. The sample is representative of the Austrian population in terms of gender, age, and residential area (see Statistics Austria, 2010). The group of purely globally oriented consumers in the sample was small, while the majority of respondents classified themselves as being glocal (see Appendix 2, first column).

3.2. Measures and CMB

For GCO, Alden et al.’s (2006) forced-choice measure was used (see Appendix 1). Rather than assessing GCO across all five consumption-related domains (lifestyle, entertainment, furnishings, clothing, and food), the present study included the GCO lifestyle domain only. The lifestyle domain represents the broadest GCO category and includes many consumption-related aspects that are consistent across product categories. This restriction to one category considerably shortened and simplified the questionnaire for respondents, and it is justified by the assumption of attitudinal consistency across consumption contexts (Alden et al., 2006; Zhou & Belk, 2004).

Appendix 1 lists the scales used for GA, global brand evaluation, global brand attitude, purchase intention, perceived brand globality, and brand familiarity. All scales were translated and back-translated from English into German by bilingual translators (Behling & Law, 2000). A pre-test of ten consumers using the protocol approach (Diamantopoulos & Reynolds, 1998) ensured that all items were comprehensible and that no difficulties in answering occurred. All scales yielded Cronbach’s alpha values above .7 (see Table 1). Finally, the questionnaire incorporated perceived brand origin (“Austria” or “other country” without specifying a foreign country) as a control variable as well as demographic variables (sex, age, education, residential area).

Coca Cola was selected as the global brand with foreign origin, and Red Bull as the global brand with domestic origin. Coca Cola was highly familiar to respondents (mean = 6.53 (s.d. = 1.14), perceived as global in reach and awareness (mean = 6.27 (s.d. = 1.19)), and correctly identified as foreign. Red Bull was also highly familiar to respondents (mean = 5.76 (s.d. = 1.95), perceived as global in reach and awareness (mean = 5.46 (s.d. = 1.68), and correctly identified as domestic. To control for common method bias (CMB), predictor and criterion variables were allocated in separate sections of the questionnaire, verbal labels were used for scale mid-points, and the scale format was varied using Likert scales and semantic differentials (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). To statistically control for CMB, we adopted a partial correlation technique (Lindell & Whitney, 2001) using a theoretically unrelated marker variable (“In my opinion, the existence of the legal penalty in some countries is to accept/to condemn”, measured on a 7-point semantic scale). Bivariate correlations among the marker and the other variables as well as a series of partial correlations showed no indication for severe problems of CMB.

### Table 1

Focal constructs: means, standard deviations and Cronbach’s alphas.

<table>
<thead>
<tr>
<th></th>
<th>Study I Mean (s.d.)</th>
<th>Cronbach’s alpha</th>
<th>Study II Mean (s.d.)</th>
<th>Cronbach’s alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA</td>
<td>3.99 (1.25)</td>
<td>.78</td>
<td>4.74 (1.04)</td>
<td>.75</td>
</tr>
<tr>
<td>GBA foreign</td>
<td>4.60 (1.75)</td>
<td>.83</td>
<td>4.85 (1.17)</td>
<td>.94</td>
</tr>
<tr>
<td>GBA domestic</td>
<td>4.02 (2.00)</td>
<td>.82</td>
<td>5.39 (1.21)</td>
<td>.91</td>
</tr>
<tr>
<td>GBE foreign</td>
<td>5.38 (1.22)</td>
<td>.78</td>
<td>5.17 (1.01)</td>
<td>.89</td>
</tr>
<tr>
<td>GBE domestic</td>
<td>5.13 (1.41)</td>
<td>.84</td>
<td>5.57 (0.98)</td>
<td>.83</td>
</tr>
<tr>
<td>PI foreign</td>
<td>3.05 (2.03)</td>
<td>.87</td>
<td>3.67 (1.69)</td>
<td>.97</td>
</tr>
<tr>
<td>PI domestic</td>
<td>2.60 (1.20)</td>
<td>.87</td>
<td>4.02 (1.80)</td>
<td>.96</td>
</tr>
</tbody>
</table>

GBA...Global Brand Attitude, GBE...Global Brand Evaluation, PI...Purchase Intention.

3.3. Discriminant validity

Due to the single-item measure of GCO, the Fornell and Larcker (1981) criterion was not applicable to test for discriminant validity between GCO and GA. Instead, a dyadic approach was used. First, the inter-construct correlation yielded a medium inter-construct correlation of phi = .28 (which corresponds to a shared variance of 7.8% between constructs), supporting both the expected positive correlation and the distinct nature of the two constructs. Second, the single-item GCO measure was modeled as an additional indicator of the GA construct in a CFA. This model explained only $R^2 = .08$ of the indicator variance (while $R^2$ values of the other indicators ranged between .66 and .84) and provided additional support for the theoretical assumption of conceptual distinctiveness. In sum, GCO and GA were shown to be conceptually and empirically distinct.

Discriminant validity was also tested for the modeled belief–attitude–intention sequence of outcome variables (see Fig. 1). As Appendix 3 shows, discriminant validity was established for all constructs, as AVEs of the individual constructs are all higher than the squared correlations between the relevant constructs.¹

3.4. Model results

3.4.1. Rival models and moderation of brand origin

Because the simultaneous inclusion of all direct effects in the model shown in Fig. 1 would violate statistical model identification rules (Hess, 2001), we took a two-step approach. First, we tested a rival model that included additional direct paths emanating from GA (Rival Model A). Second, we re-ran the analysis based on Fig. 1 and included the additional direct paths emanating from GCO (Rival Model B). Using this approach, we were able to test for direct effects without compromising statistical model identification. Based on the results of chi-square difference tests,² a direct path from GCO to global brand attitude was added to the theoretical model for the domestic global brand (see Fig. 2a), and a direct path from GA to purchase intention was added to the theoretical model for the foreign global brand (Fig. 2b).

To formally test the moderating effect of global brand origin, we conducted a multi-group analysis in LISREL 8.80 that included both additional direct relationships.³ A chi-square difference test comparing a model with free structural parameter estimates ($\chi^2 (138) = 373.61$) to one with fixed structural parameters ($\chi^2 (149) = 399.92$) was significant ($\Delta \chi^2 (11) = 26.31, p < .01$), and thus supported the distinction of the domestic and foreign brand models.

3.4.2. Parameter estimates

GA positively impacts brand evaluation for both domestic and foreign global brands (see Table 2, columns 1 and 2), thus supporting H1. GCO also shows a positive relationship to global brand evaluation for the foreign global brands (see Table 2, columns 1 and 2), thus supporting H2. In addition, GCO positively relates to brand attitude for the domestic global brand; thus, we find only partial support for H2. In addition, GCO positively relates to purchase intentions for the foreign global brand.

¹ Appendix 3 also demonstrates discriminant validity between GA and consumer ethnocentrism (Shimp & Sharma, 1987), consumer cosmopolitanism (Riefler & Diamantopoulos, 2009), and susceptibility towards normative influences (Bearden, Nette- meyer, & Teel, 1989), which were also assessed in Study I. We thank the editor for her suggestion to include this information.

² Detailed results on the chi-square difference tests are available upon request.

³ Additionally, we included brand dummies in the pooled data models, which were non-significant and therefore dropped to safeguard model simplicity.
The hypothesized mediated relationships were tested following Zhao, Lynch, and Chen’s (2010) recommended approach using bootstrapping (based on 1000 bootstrap resamples) to investigate the significance of indirect effects. According to this approach, an indirect effect is significant, and mediation is established, if the bootstrap confidence interval of an indirect effect does not include 0 (Preacher & Hayes, 2008; Zhao et al., 2010). In line with H3a, global brand evaluation fully mediates the positive relationship of GA to global brand attitude for both brands (Table 2). In line with H4a, the relationship of GA to purchase intentions is mediated by global brand evaluation and global brand attitude. For the domestic global brand this double mediation represents an indirect-only effect, whereas for the foreign global brand, it is complementary (Zhao et al., 2010) to the positive direct effect of GA on purchase intention. With regard to GCO, the expected indirect effect on global brand attitude is not significant for the domestic brand; GCO has a direct-only effect on brand attitude. For the foreign global brand, in contrast, the expected indirect effect is significant and represents an indirect-only effect. Hence, H3b is supported for the foreign global brand but not supported for the domestic brand. Finally, for both brands, GCO shows a significant indirect-only effect on purchase intentions that is mediated by global brand evaluation and global brand attitude; thus, H4b is supported.

3.4.3. Contrasting findings

Comparing the findings for the two types of global brands reveals interesting similarities and differences. With regard to similarities, first, the two models explain considerable portions of variance in the outcome variables (see Table 2, bottom).4 Second, GA strongly relates

![Diagram](image-url)
to brand evaluations for both brands, and this provides support for the hypothesized contingency of consumers’ attitudes towards economic globalization for positive global brand evaluations. Third, GCO does not directly relate to purchase intentions but instead affects the latter indirectly through brand evaluation and attitudes. Fourth, GA does not directly influence brand attitudes in either of the two models, and this suggests that there is no attitude transfer from the general stance towards economic integration to the attitude towards specific global brands. Instead, the attitude change is fully mediated by a more positive or more negative brand evaluation.

GCO, in contrast, appears to strongly and directly influence attitudes toward the domestic global brand. The hypothesized attitude transfer from the consumption orientation to the specific brand is thus present. Interestingly, with regard to the differences between the two models, such a direct attitude transfer is not found for the foreign brand. For the latter, the effect of a strong GCO is fully mediated by a more positive evaluation of the foreign global brand. With regard to differences in the effect patterns of GA between the two models, GA directly affects purchase intentions only for the foreign brand. Global brands from the home country, in contrast, do not seem to face direct effects on purchase intentions. Purchase intentions for these brands are affected via lower (higher) brand evaluations and, consequently, brand attitudes.

4. Study II: Replicating the models using Palmers (domestic) and Intimissimi (foreign)

In Study I, the global brand models for foreign and domestic brands were tested for soft drinks, a FMCG product category characterized by low consumer involvement and hedonic elements. In Study II, we extend the models to a second product category, lingerie, which is durable and thus characterized by higher consumer involvement.

4.1. Data collection and measures

In cooperation with a professional consumer online access panel provider, 150 Austrian consumers (with quotas for sex, age, and education) were recruited for participation. Within the sample, 53% were females, the average age was 41.6 years (range: 15 to 74 years), and 28% had a higher education (high school or university degree).

The questionnaire incorporated the same measures as in Study I. In addition, we included Steenkamp and de Jong’s (2010) measure of attitude towards global products (AGP). AGP intends to capture a generalized attitude towards global products across product categories and should thus overcome any potential conceptual limitations of the GCO lifestyle domain measure. As in Study I, the majority of respondents allocated themselves to the global group of the GCO measure; the same was true for the AGP measure (see Appendix 2).

The lingerie brands, Palmers and Intimissimi, were chosen based on a pre-study testing of various domestic and foreign brands regarding consumer brand familiarity, perceived domestic/foreign origin, and perceived globalization, using a convenience sample of 50 Austrian consumers. Palmers was familiar to respondents (mean = 5.89, s.d. = 1.36) and clearly perceived as global in awareness and reach (mean = 5.54, s.d. = 1.23). At this point, it should be emphasized that brand globalization is defined by consumer perception (Özsomer & Altaras, 2008). Even if Palmers might not be familiar to consumers worldwide, the perception of Austrian consumers of Palmers as a brand with global awareness and reach is relevant for the current study. Intimissimi was also very familiar to respondents (mean = 4.88, s.d. = 1.62) and perceived as global in awareness and reach (mean = 5.19, s.d. = 1.17). Respondents correctly identified Palmers and Intimissimi as domestic and non-domestic, respectively.

CMB was tested as in Study I using Lindell and Whitney's (2001) partial correlation technique. The marker variable used in Study II (“How often do you read your horoscope?”, measured on a 5-point frequency scale) captured a personal habit that was theoretically expected as unrelated to the focal constructs of our model. Bivariate correlations among the marker and the other variables as well as a series of partial correlations showed no indication for severe problems of CMB. Finally, discriminant validity between GA and the AGP measure was established (see Appendix 3).

4.2. Model results

To test the generalizability of the findings in Study I, we engaged in a two-step approach. First, we replicated the models for domestic and foreign global brands using the fresh data on Palmers and Intimissimi. Second, we stacked data from Studies I and II to test for product category effects (Fischer, Voelckner, & Sattler, 2010).

4.2.1. Main and mediated effects

The domestic global brand model (Fig. 2a) yielded an acceptable fit for the Palmers brand (χ²(56)=94.47; RMSEA = .076; SRMR = .057; NNFI = .963; CFI = .973), while the foreign global brand model (Fig. 2b) showed good fit for the Intimissimi brand (χ²(56)=57.52; RMSEA = .019; SRMR = .051; NNFI = .996; CFI = .997). For the domestic global brand model, the results from Study I are replicated (Table 3, column 1). GA positively impacts global brand evaluation, which provides additional support for H1. GCO positively, but not significantly, relates to brand evaluation, which

<table>
<thead>
<tr>
<th>Table 3 Study II: Parameter estimates (standardized structural coefficients) and variance explained (R²).</th>
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</thead>
<tbody>
<tr>
<td><strong>Domestic Global Brand (Palmers)</strong></td>
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<tr>
<td><strong>Foreign Global Brand (Intimissimi)</strong></td>
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<tr>
<td><strong>Direct effects</strong></td>
</tr>
<tr>
<td>GA → GBE (H1: +)</td>
</tr>
<tr>
<td>GCO → GBE (H2: +)</td>
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<tr>
<td>GCO → PI ( +)</td>
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<tr>
<td>GBE → GBA ( +)</td>
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<tr>
<td>GBA → PI ( +)</td>
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<tr>
<td><strong>Covariates</strong></td>
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<tr>
<td>Brand familiarity → GBE ( +)</td>
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<tr>
<td>Brand familiarity → GBA ( +)</td>
</tr>
<tr>
<td>Brand familiarity → PI ( +)</td>
</tr>
<tr>
<td>Brand globalization → GBE</td>
</tr>
<tr>
<td>Brand globalization → GBA</td>
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<tr>
<td>Brand globalization → PI</td>
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<tr>
<td><strong>Indirect effects</strong></td>
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<tr>
<td>GA → GBE → GBA (H3a)</td>
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<tr>
<td>GA → GBE → PI (H4a)</td>
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<tr>
<td>GCO → GBE → GBA (H5b)</td>
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<tr>
<td>GCO → GBE → PI (H5b)</td>
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<tr>
<td><strong>Variance explained (R²)</strong></td>
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<tr>
<td>Brand evaluation</td>
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<tr>
<td>Brand attitude</td>
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<tr>
<td>Purchase intention</td>
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</tbody>
</table>


*** p < .001.
** p < .01.
* p < .05.

* Point estimates. Lower and upper bootstrapping confidence intervals in (). Confidence intervals containing zero are interpreted as not significant (ns).
again does not clearly support H2. Finally, the positive direct effect of GCO on domestic brand attitude is again found. With regard to mediated effects, in line with findings from Study I, H3a, H4a and H4b are supported (see Table 3, column 1).

For the foreign global brand model, as in Study I, GCO positively influences brand evaluation (Table 3, column 2), which provides further support for H2. With regard to mediated effects, the positive effect of GCO on brand attitude is fully mediated by brand evaluation, which again supports H3b. The effects of GCO and GA on purchase intention are fully mediated by global brand evaluation and global brand attitude, thus providing further support for H4a and H4b. GA, in contrast, fails to show any significant direct effect on brand evaluation (not providing further support for H1) or any mediated effect on brand attitude (not providing further support for H3a).

Overall, the results in Study II confirmed the majority of the findings of Study I. The major difference found between the studies was a lack of influence of GA in the context of the foreign lingerie brand. To isolate any product category effects that potentially cause these differences, we tested for interaction effects of the product category as a final step.5

4.2.2. Product category effects

The tested product categories differ in product complexity, costs and consequently in consumer involvement, which is seen as an important moderator for various influences on purchase decisions (e.g., Celsi & Olson, 1988; Sub & Yi, 2006). Using a pooled dataset, we ran two separate LISREL models to test for product category effects, namely (1) the domestic global brand model (based on data for Red Bull and Palmers), and (2) the foreign global brand model (based on data for Coca Cola and Intimissimi). We added interaction effects of product category for GCO and GA on all relevant outcome variables.6

As Table 4 shows, all included interaction effects are significant. For both foreign and domestic global brands, high positive interaction effects reveal that GA relates more strongly to brand evaluation and purchase intention for the lingerie category than for the soft drink category.

Table 5 summarizes the main results of both studies. It shows that, with two exceptions, the results are quite consistent. With regard to the first exception, the main effect of GCO on brand evaluation was, as expected, positive for all (domestic and foreign) global brands; however, the relationship did not achieve significance in all cases. With regard to the second exception, the direct effect of GA on global brand evaluation and purchase intention was not replicated in Study II. As the interaction effect with the product category is negative (Table 4), this direct effect on the outcome variables appears to be more relevant for the low-involvement category. This result suggests that FMCGs might be more affected by globalization attitudes because they can be more easily avoided by consumers given the (non-global) alternatives in the market. For example, there are a number of other cola drinks available in the Austrian market, which enables consumers to avoid Coca Cola. For the lingerie brand, consumers are more restricted in choice, so the sacrifice they incur from a boycott might be stronger (Klein, Smith, & John, 2004).

5 We thank the editor for this suggestion.

6 We added interaction effects between the dummy variable denoting the product category of a brand (0 = soft drink, 1 = lingerie) and the focal constructs (GA and GCO). Based on the models shown in Fig. 2, the interaction model included only relevant interaction effects on the outcome variables (as listed in Table 4).
contingent on consumers’ attitude towards globalization. Those who disfavor economic integration evaluate global brands less positively, irrespective of their domestic or foreign origin. The results further suggest that this discount is particularly relevant for high-involvement products. Considering that consumers are in general positively biased in the evaluation of domestic brands (Balabanis & Diamantopoulos, 2004), this finding suggests that a global appeal can additionally enhance the evaluation of domestic brands, provided that globalization is perceived positively.

Moreover, for domestic global brands, brand evaluation fully mediates the effects of GA on brand attitudes and purchase intentions. This result suggests that consumers do not use domestic brands to take a stance in the globalization debate. Instead, their positive (negative) attitudes towards economic integration primarily impact their assessments of global brands, and this assessment affects their attitudes and behavioral intentions only as a consequence. Foreign global brands, in contrast, can directly benefit or suffer from consumers’ attitudes towards economic globalization, as purchase intentions for these brands are directly affected.

With regard to GCO, overall, the results suggest that consumers with strong GCO use brand globalness as a quality signal. This means of simplifying and speeding up the decision process is particularly used for low-involvement categories where decision time pressure is high and the financial risk of making a wrong choice is low (Erdem & Swait, 2004). The findings also partially substantiate Alden et al.’s (2006) study by showing that consumers with a strong GCO have more positive brand attitudes for domestic, but not foreign, global brands. It seems that globally oriented consumers can more easily identify with globally successful companies from their home country as companies that are “one of us” that have “made it”. Hence, the findings suggest that a global brand positioning strategy can serve as a competitive advantage in domestic markets with a globalization-friendly atmosphere. Brand attitudes for foreign global brands benefit indirectly through more positive brand evaluations.

Overall, the empirical studies showed that the key factor for global brands is brand evaluation, which mediates all positive and negative effects of consumers’ GA and GCO. Domestic global brands additionally benefit (suffer) in terms of brand attitude from identity (in)congruity of (non)global consumers, while foreign global brands are potentially used to taking a positive or negative stance in the globalization debate.

5.2. Theoretical contributions

The theoretical contribution of the present study is two-fold. First, it shows that brand origin is relevant for global brands, and it thus contributes to the recent scholarship on local versus global brands in the global branding literature (e.g., Van Ittersum & Wong, 2010; Zhang & Khare, 2009). Empirically, the differentialization of domestic and foreign brands with global appeal is substantiated by divergent effect patterns which suggest that global brands should not be investigated independently of their associated brand origin.

Second, the paper empirically relates both GA and GCO to Fishbein and Ajzen’s (1975) belief–attitude–behavior hierarchy and compares their direct and mediated effects using a set of real brands. The paper shows that GA and GCO are related but conceptually discriminate constructs, which have distinct influences on brands. Consequently, models intending to explain consumers’ response to global offers should incorporate both constructs. The use of the hierarchy of effects is empirically validated by (a) demonstrating discriminant validity between global brand evaluation, global brand attitude and purchase intention, and (b) differing direct and mediated effects of the exogenous variables on the three outcome variables.

5.3. Managerial implications

The assumption that all consumers become global in their orientation because companies do so has proven untenable (Suh & Kwon, 2002). Marketing managers face more complex consumer responses to globalization and global brands than initially assumed (Van Ittersum & Wong, 2010). The findings of our study suggest that countries with large pro-global consumer segments are naturally more attractive targets for global companies. Importantly, the findings further reveal that companies gain a competitive advantage from global positioning not only in foreign markets but also in domestic markets among consumer segments oriented towards globalization. Within countries, parallel strategies could be fruitful if the market size of pro-global and anti-global consumer segments warrants the associated duplication of costs. Alternatively, the findings suggest that efforts towards localizing global brands to target globalization-friendly countries or segments could potentially lead to cost savings, as these consumer groups welcome globalization.

However, mainly as a result from recent financial crises, recessions, and unemployment, major markets, such as the European Union or the US, currently tend to exhibit negative attitudes towards globalization (e.g., Meunier, 2010). Given this challenging situation, global companies should support initiatives that aim at fostering positive globalization attitudes because such attitudes are beneficial to them. Such initiatives might, for example, include joint campaigns of companies or organizations highlighting the economic, social, and political benefits of international integration and cooperation.

6. Limitations and directions for future research

A number of potential directions for future research can be identified. First, the present study uses Alden et al.’s (2006) lifestyle domain to assess GCO, which was the broadest category and legitimized by attitudinal consistency across consumption contexts (Alden et al., 2006; Zhou & Belk, 2004). Given that different product categories were included, similar studies should assess all five GCO domains (lifestyle, food, furniture, clothing, and entertainment) to further substantiate these findings.7

Second, the present article investigates the effects of GA for two hedonic product categories with differing levels of consumer involvement. Because we selected only one product category at each level of consumer involvement, further replication studies should focus on additional low- and high-involvement product categories. These should also include utilitarian product categories (as, for example, toothpaste or washing machines).

Finally, country-specific constructs such as (product) country image (Roth & Diamantopoulos, 2009), consumer animosity (Klein, Ettensohn, & Morris, 1998), or consumer affinity (Oberecker, Riefler, & Diamantopoulos, 2008) were not incorporated in the foreign global brand model. An interesting endeavor for future research is to test potential complementary or contradictory effects on brand evaluation, brand attitude, and purchase intention.

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7 To test whether the brand-related ACP measure (Steenkamp & de Jong, 2010) contributes differently than GCO to global brand evaluation, attitude and purchase intention, we ran the models for Palmers and Intmissim, adding CPA as an additional exogenous variable. CPA was modeled to directly affect all three outcome variables. For both brands, CPA was not found to have any impact on the outcome variables beyond that of GCO and GA. Indeed, none of the direct paths were shown to be significant. The other parameter estimates remained stable compared to the initial models (as reported in Table 3). These results lead to the conclusion that the GCO lifestyle domain is adequate for the lingerie product category.
Appendix 1. Measurement items

Globalization Attitude (shortened version of Spears et al., 2004)
In my opinion, increased economic globalization...
- encourages a maximum of personal freedom and choice.
- leads to quality and technical advances.
- provides consumers the goods and services they want.
Response format: 7-point Likert scale, 1 = strongly disagree, 7 = strongly agree
Global Consumption Orientation (lifestyle dimension, by Alden et al., 2006)
(1) To be honest, I do not find the typical lifestyle in my home country or the lifestyles of consumers in other countries very interesting.
(2) It is more important for me to have a lifestyle that is unique to or traditional in my home country rather than one that I think is similar to the lifestyle of consumers in many countries around the world.
(3) I try to blend a lifestyle that is considered unique to or traditional in my home country with one that I think is similar to the lifestyle of consumers in many countries around the world.
(4) It is important for me to have a lifestyle that I think is similar to the lifestyle of consumers in many countries around the world rather than one that is more unique to or traditional in my home country.
Response format: single choice; coded as 1 = no interest, 2 = local orientation, 3 = mixed orientation, 4 = global orientation

Global Brand Evaluation (Parameswaran & Pitharoudi, 1994)
- Please rate [BRAND] on the following attributes: (1) Quality, (2) Image, (3) Value for Money
Response format: 7-point semantic differentials (poor/excellent)

Global Brand Attitude (based on Alden et al., 2006)
- I think this brand is good/bad
- I have a positive/negative opinion of this brand.
Response format: 7-point semantic differentials

Purchase Intention (based on Dodds, Monroe, & Grewal, 1991 and Petruvov & Lord, 1994)
- The next time that I buy [PRODUCT CATEGORY], I will choose [BRAND].
- I will consider [BRAND] for my next purchase.
- It is very likely that I will buy [BRAND] in the future.
Response format: 7-point Likert scale, 1 = strongly disagree, 7 = strongly agree

Brand Familiarity (based on Simonin & Ruth, 1998)
- It is very likely that I will buy
- The next time that I buy
Response format: 7-point semantic differentials

Global Brand Attitude (based on Alden et al., 2006)
- I think consumers worldwide buy [BRAND].
- I think only consumers in Austria buy [BRAND].
- [BRAND] is sold only in Austria.[BRAND] is sold worldwide
Response format: 7-point semantic differentials

Appendix 2. Frequency distribution of GCO and AGP (in %)

<table>
<thead>
<tr>
<th>Study 1: GCO</th>
<th>Study 2: GCO</th>
<th>Study 2: AGP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global</td>
<td>11.6</td>
<td>10.0</td>
</tr>
<tr>
<td>Glocal</td>
<td>39.7</td>
<td>45.0</td>
</tr>
<tr>
<td>Local</td>
<td>25.2</td>
<td>18.8</td>
</tr>
<tr>
<td>Alienated</td>
<td>23.5</td>
<td>26.3</td>
</tr>
</tbody>
</table>

Appendix 3. Construct Correlations, Shared Variances, and AVEs

<table>
<thead>
<tr>
<th>GA</th>
<th>GCO</th>
<th>AGP</th>
<th>CET</th>
<th>COSMO</th>
<th>SNI</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>.57</td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>

Globalization attitude (GA) 1
Global consumption orientation (GCO) 1
Attitude towards global products (AGP) 2
Consumer ethnocentrism (CET) 3
Consumer cosmopolitanism (COSMO) 3

Note: Correlations are shown in brackets.
1 data from Study 1; 2 data from Study 2; 3 constructs were not included in the same sample; 4 AVE not applicable due to single-item measure.

References


A short 8-item scale for measuring consumers’ local–global identity

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Abstract
The development and validation of an 8-item scale for assessing consumers’ local–global identity are described in this paper. Based on six studies of student and non-student samples from three countries, we demonstrate the psychometric properties of this scale, its reliability, and discriminant and convergent validity with related constructs, such as consumer ethnocentrism, nationalism, and global consumption orientation. We also test the scale’s ability to predict consumers’ preference between local and global products.

1. Introduction
With rapid globalization, local and global products are routinely pitted against each other. Although global products are growing stronger (Alden, Steenkamp, & Batra, 1999; Gürhan-Canli & Maheswaran, 2000), local products are successfully competing against these global products (Parmar, 2004; Rigby & Vishwanath, 2006). Consider the success of two local colas, Mecca Cola in France and Fei-Chang Cola in China, alongside the two global colas, Pepsi and Coke. There appears to be both local and global leanings in consumers’ product judgments. A study by Zhang and Khare (2009) showed that identifying consumers’ identity as global or local is key to understanding consumers’ attitudes toward global versus local products. Thus, the study suggests that managers need to understand whether consumers feel they are part of a global or local community to manage the positioning of global versus local products.

A local identity means that consumers feel they belong to their local community and identify with local ways of life, whereas a global identity means that consumers feel they belong to the global community and identify with a global lifestyle. The local–global identity construct was proposed by psychologist Arnett (2002) to discuss the psychological consequences of globalization. Following this conceptualization, Zhang and Khare (2009) proposed a 19-item scale to empirically measure the construct. Because Zhang and Khare’s main focus was on issues pertaining to the accessibility and diagnosticity of the construct, they did not employ traditional scale development procedures. In this research, our objectives are not only to shorten their 19-item scale for better usability but also to apply scale development procedures systematically.

In an increasingly globalized world, consumers’ global and local identities are important for their product decisions. Thus, understanding the consequences of these identities is important for marketing practices, such as when managers must decide between a global or local positioning strategy for their brands. For example, how should Coke position itself in the Chinese market? As a global brand? As a local brand? Or as both global and local? We believe that a global positioning strategy is needed where global identification is strong, and a local positioning strategy is appropriate where local identification is strong. More generally, many marketers need to decide between global and local products. Whereas local products are made with specifications and packaging tailored for local markets, global products are made with similar specification and packaging for consumers from around the world (Steenkamp, Batra, & Alden, 2003; Zhang, Feick, & Mittal, 2005).

Thus, from both managerial and theoretical perspectives, it is important to understand the local–global identity construct and to have a good measure of this construct. In line with this need, we propose an 8-item scale for a local–global identity measurement. Following standard scaling procedures (e.g., Netemeyer, Bearden, & Sharma, 2003), we propose and test items for such a scale, and demonstrate its ability to explain consumers’ preference between local and global products.

We believe that our research offers key contributions to the global identity literature and implications for managerial practice. First, although Arnett’s (2002) pioneering research on the psychology of globalization delineates the conceptual framework for a local–global identity, efforts to measure it have been lacking (with Zhang & Khare, 2009 an exception). We propose and test scale items for this identity and believe that this will help to advance the emergent research in this important consumer domain.

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Second, we provide an improvement in ease of use over Zhang and Khare's (2009) 19-item scale. Their scale is an important introduction in the still emerging local–global identity research area. However, the length of their 19-item scale is cumbersome, and time considerations may reduce the frequency of its use. Our proposed scale has fewer items, but comparable reliability and predictive validity. We believe our scale will further facilitate the research and measurement of the local–global identity construct in practice.

Third, we test our scale with student and non-student samples from three different countries and consistently demonstrate that consumers have local and global identities. Zhang and Khare's (2009) study used U.S. student samples only. Thus, we believe that our non-student, international samples significantly add to the generalizability of their conclusions.

Fourth, we establish the discriminant and convergent validity of the local–global identity construct, which was only alluded to by Zhang and Khare (2009). We show that the local–global identity construct is related to but also very different from constructs such as consumer ethnocentrism, nationalism, and global consumption orientation. The conceptual connection between the local–global identity and global consumption orientation constructs has been suggested in the literature (Steenkamp & de Jong, 2010) but had not been empirically tested. Our results show that investigating the connections between these constructs helps to fully understand the consequences of globalization on consumers' product preferences.

Lastly, our results have key implications for managerial practice. By understanding consumers' local–global identity affiliations, marketers may be better able to decide between a local or global positioning strategy not just for their products but also for their services and customer outreach efforts such as corporate social responsibility (CSR). Noticing much stronger local identity among Chinese customers compared to their American counterparts, Timberland, a manufacturer of footwear products, focuses its CSR efforts on Chinese environmental causes for Chinese customers but on global environmental causes for American customers (Veatch, 2010). Original equipment manufacturers, such as HTC (now the No. 1 maker of Android handsets), realize that an increasing number of global customers are buying products with their components and have invested heavily in marketing to develop their own global brands, rather than continuing to play second-fiddle to the retailers they sell to (Roberts & Leung, 2010). The marketing efforts of companies such as Timberland and HTC could be strengthened if they had a direct way of gauging the extent of localness or globalness among their consumers. Our short, 8-item local–global identity scale can be a very convenient tool for this purpose.

2. Local–global identity: Conceptual background

Social-identity research indicates that when an identity is accessible (i.e., its mental representations are salient), individuals respond favorably to stimuli consistent with the accessible identity. For instance, research on ethnicity (Deshpandé & Stayman, 1994; Forehand, Deshpandé, & Reed, 2002) has found that when consumers’ ethnic identity is accessible, they respond more favorably to advertisements in which a spokesperson’s ethnicity is consistent with their own ethnic identity. In the context of cultural identity, Aaker (2000; Aaker, Benet-Martinez, & Goralera, 2001) have found that brand associations consistent with consumers’ cultural identity induce a more favorable attitude toward the advertised brands. Overall, accessibility effects occur because consumers like to hold positive selfviews, and thus, identity-consistent information is judged as more relevant for processing objectives and is given greater weight than identity-inconsistent information (Wheeler, Petty, & Bizer, 2005).

Arnett (2002) proposes that consumers tend to have both local and global identities. A local identity consists of mental representations in which consumers have faith in and respect for local traditions and customs, recognize the uniqueness of local communities, and are interested in local events. A global identity consists of mental representations in which consumers believe in the positive effects of globalization, recognize the commonalities rather than dissimilarities among people around the world, and are interested in global events.

3. Study 1: Shortening Zhang and Khare's 19-item local–global identity scale

To shorten the 19-item scale proposed by Zhang and Khare (2009), we looked at the exploratory factor structure in their paper and selected five items with the highest factor loadings from both the global and local subscales (for a total of ten items).

We then formed an expert panel to help in further shortening the list. Sixteen individuals (marketing professors and doctoral students from two large universities in the southwestern U.S.) with knowledge about scale development were provided with Arnett’s (2002) definition of the local–global identity construct so as to make sure that all panelists had the same understanding of the construct. Specifically, the panelists received the following explanation: “What are global and local identities? Local identity means that consumers feel that they belong to their local community and identify with their local ways of life; while global identity means that consumers feel that they belong to the entire world and identify with a global lifestyle.” The panelists were then asked to rate each of the 10 items we had shortlisted on a 7-point scale (1 = Definitely Include, ..., 7 = Definitely Exclude) and to list two items they wanted to drop. Based on the panelists’ responses, we decided to drop two of the ten items: “I like to know about people in other parts of the world,” and “I can more easily find like-minded people within my community than outside.” These two items had both lower exclusion-inclusion ratings (4.8 and 3.3) than the ratings for the other eight items (which ranged from 4.9 to 6.2 for the other eight items) and were also the most likely items for panelists to drop.

In this way, we came up with eight items (with minor wording changes) for our shorter local–global identity scale (see Table 1). The four items for global identity are (1 = Strongly Disagree, 7 = Strongly Agree): “I care about knowing global events,” “My heart mostly belongs to the whole world,” “I believe that people should be made aware of how connected we are to the rest of the world,” and “I identify that I am a global citizen”. The four analogous items for local identity are (1 = Strongly Disagree, 7 = Strongly Agree): “I care about knowing local events,” “My heart mostly belongs to my local community,” “I respect my local tradition,” and “I identify that I am a local citizen.” As social identities have been defined as “being, belonging, and becoming” (Arnett, 2002; Forehand et al., 2002), we think our eight items capture these aspects of global and local identities.

3.1. Sample description

Table 1

<table>
<thead>
<tr>
<th>Local–global identity scale: factor loadings.</th>
<th>Factor loading</th>
</tr>
</thead>
<tbody>
<tr>
<td>Items</td>
<td>Factor 1</td>
</tr>
<tr>
<td>My heart mostly belongs to the whole world.</td>
<td>.847</td>
</tr>
<tr>
<td>I believe people should be made more aware of how connected we are to the rest of the world.</td>
<td>.879</td>
</tr>
<tr>
<td>I identify that I am a global citizen.</td>
<td>.854</td>
</tr>
<tr>
<td>I care about knowing global events.</td>
<td>.780</td>
</tr>
<tr>
<td>My heart mostly belongs to my local community.</td>
<td>.147</td>
</tr>
<tr>
<td>I respect my local traditions.</td>
<td>.130</td>
</tr>
<tr>
<td>I identify that I am a local citizen.</td>
<td>.135</td>
</tr>
<tr>
<td>I care about knowing local events.</td>
<td>.295</td>
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</tbody>
</table>
item scale. The response rate was 7%. The participants in this study represented a broad cross-section of consumers. Their ages ranged from 18 to 75, 42% were men, their education levels ranged from completion of high school or below to a graduate degree, family size ranged from 1 to 6, and 70% identified themselves as middle class.

3.2. Factor structure

Two analytic steps were completed to determine the factor structure of the proposed 8-item scale. First, an exploratory factor analysis (EFA) was completed on the local–global identity items. A principal component analysis and varimax rotation yielded two factors with eigenvalues greater than 1.00. These two factors accounted for 73.68% of local–global identity variance. Factor loadings for individual items are summarized in Table 1.

To further test the factor structure, a subsequent confirmatory factor analysis (CFA, LISREL 8.80) was conducted by creating structural equation models that corresponded with the item-factor loadings that emerged in the EFA. We compared three models. Local–global identity in model 1 was constructed as a single factor ($\chi^2 (20) = 421.80$, $p < .001$, CFI = .62, GFI = .63, RMSEA = .30). Model 2 constructed local–global identity as two uncorrelated factors ($\chi^2 (20) = 173.32$, $p < .001$, CFI = .86, GFI = .85, RMSEA = .19). Model 3 constructed local–global identity as two correlated factors ($\chi^2 (19) = 127.78$, $p < .001$, CFI = .90, GFI = .89, RMSEA = .16). Model 3 fits significantly better than the first model ($\Delta \chi^2 (1) = 294.02$, $p < .001$) and the second model ($\Delta \chi^2 (1) = 45.54$, $p < .001$). The reliabilities of both the local identity and global identity subscales were satisfactory ($\alpha_{\text{Local}} = .87$ and $\alpha_{\text{Global}} = .89$). These results indicate that our local–global identity scale includes two correlated yet separate factors. Detailed correlations between the two subscales can be found in Table 2.

To summarize, this study shows that our proposed 8-item scale includes two correlated yet separate factors, and this result is similar to what we found using Zhang and Khare's (2009) 19-item scale (they did not conduct these tests). Next, we test the reliability of our proposed 8-item scale.

4. Study 2: Test–retest reliability evidence

In this study, we test the internal and temporal reliability of our 8-item scale.

4.1. Participants and procedures

Forty-three undergraduate students from a large southwestern U.S. university participated in this study for extra course credit.

4.2. Factor structure

To test the factor structure, a confirmatory factor analysis (CFA, LISREL 8.80) was conducted by creating structural equation models that corresponded with the item-factor loadings that emerged in the EFA. We compared three models. Local–global identity in model 1 was constructed as a single factor ($\chi^2 (20) = 421.80$, $p < .001$, CFI = .62, GFI = .63, RMSEA = .30). Model 2 constructed local–global identity as two uncorrelated factors ($\chi^2 (20) = 173.32$, $p < .001$, CFI = .86, GFI = .85, RMSEA = .19). Model 3 constructed local–global identity as two correlated factors ($\chi^2 (19) = 127.78$, $p < .001$, CFI = .90, GFI = .89, RMSEA = .16). Model 3 fits significantly better than the first model ($\Delta \chi^2 (1) = 294.02$, $p < .001$) and the second model ($\Delta \chi^2 (1) = 45.54$, $p < .001$). The reliabilities of both the local identity and global identity subscales were satisfactory ($\alpha_{\text{Local}} = .87$ and $\alpha_{\text{Global}} = .89$). These results indicate that our local–global identity scale includes two correlated yet separate factors. Detailed correlations between the two subscales can be found in Table 2.

To summarize, this study shows that our proposed 8-item scale includes two correlated yet separate factors, and this result is similar to what we found using Zhang and Khare’s (2009) 19-item scale (they did not conduct these tests). Next, we test the reliability of our proposed 8-item scale.

4. Study 2: Test–retest reliability evidence

In this study, we test the internal and temporal reliability of our 8-item scale.

4.1. Participants and procedures

Forty-five undergraduate students from a large southwestern U.S. university participated in this study, which was conducted over two weeks in exchange for extra course credit. In week 1, the participants completed the 8-item local–global identity scale and other unrelated scales. In week 2, the participants completed the 8-item local–global identity scale again. Detailed correlations between subscales can be found in Table 3.

The week 1 and week 2 subscales for local and global identity had significant internal reliabilities (week 1: $\alpha_{\text{Local}} = .69$, $\alpha_{\text{Global}} = .80$; week 2: $\alpha_{\text{Local}} = .79$, $\alpha_{\text{Global}} = .81$) and were therefore averaged to form a composite for each subscale in each week. Temporal reliability was also noted by the statistically significant correlations between week 1 and week 2 composite scores ($r_{\text{Local}} = .81$, $p < .05$; $r_{\text{Global}} = .89$, $p < .05$). We next test the discriminant and convergent validity of our proposed local–global scale.

5. Study 3: Tests of discriminant and convergent validity

The purpose of this study is to establish discriminant and convergent validity of the 8-item local–global identity scale by comparing it with conceptually related constructs such as nationalism and global consumption orientation.

5.1. Participants and procedures

Two hundred and fifty-three undergraduate students from a large southwestern U.S. university participated in this study for extra course credit.

5.2. Measures

5.2.1. Local–global identity

The 8-item local–global identity scale was the same as in studies 1 and 2.

5.2.2. Nationalism

Nationalism was measured with a 7-item scale (1 = Strongly Disagree, 7 = Strongly Agree) based on the works of Kosterman and Feshbach (1989) and Blank and Schmidt (2003). Examples of items in this scale include “I am proud to be American.” “The fact that the United States is the superpower in the world makes me feel proud,” and “For me, the United States is the best country in the world.” Nationalism was conceptualized as the idealization and uncritical evaluation of one’s nation (Kosterman & Feshbach, 1989) and an overemphasis of national affiliation in the individual’s self-concept (Adorno, Frenkel-Brunswik, Levinson, & Sanford, 1950). Therefore, nationalism might be conceptually related to local identity.

5.2.3. Global consumption orientation (GCO)

Global consumption orientation (Alden et al., 2006) identifies four attitudes toward global diffusion on consumption: assimilation (i.e., substituting global influence for local cultures), separation (i.e., maintaining local culture), hybridization (i.e., integrating global culture into local culture), and lack of interest. GCO is measured by responses to four central consumption-related domains: lifestyle, entertainment, furnishings, and clothing. According to the conceptualization, assimilation of GCO is comparable with global identity, whereas separation is comparable with local identity. The items measuring assimilation included the following (1 = Strongly Disagree, 7 = Strongly Agree): “It is important for me to have a lifestyle that I think is similar to the lifestyle of consumers in many countries around the world rather than one that is more unique to or traditional in my country,” “I enjoy entertainment that I think is popular in many countries around the world more than traditional forms of entertainment that are popular in my own country,” “I prefer to have home furnishings that I think are popular in many countries around the world rather than furnishings that are considered traditional in my own country,” and “I prefer to wear clothing that I think is popular in many countries around the world rather than clothing traditionally worn in my own country.” The following items measured separation (1 = Strongly Disagree, 7 = Strongly Agree): “It is more important for me to have a lifestyle that is unique to or traditional in my country rather than one that I think is similar to the lifestyle of consumers in many countries around the world.”
countries around the world.” “Entertainment that is traditional in my own country is more enjoyable to me than entertainment that I think is popular in many countries around the world.” “I like to furnish my home with traditional items from my culture more than with furnishings that I think are popular in many countries around the world,” and “I would rather wear clothing that is traditionally popular in my own country than clothing that I think is popular with consumers in many countries around the world.” Detailed correlations between the subscales can be found in Table 4.

5.3. Results

5.3.1. Discriminant validity

To establish discriminant validity of the local–global identity construct, confirmative factor analysis (CFA, LISREL 8.80) tests were performed on three pairs of subscales measuring 1) local identity versus nationalism, 2) global identity versus GCO assimilation, and 3) local identity versus GCO separation.

Following Anderson and Gerbing’s (1988) approach to discriminant validity, we conducted a series of chi-square difference tests between the two models. Model 1 is a constrained two-factor model where the correlation between the local (or global) identity subscale and the other focal discriminant scale is fixed to 1. Model 2 is an unconstrained model where the correlation is released, and thus, it is a three-factor model. Discriminant validity is supported if the three-factor model fits significantly better than the two-factor model. We also conducted the Anderson and Gerbing (1988) confidence interval test for each pair of constructs involving the local–global identity factors, and the conclusions were the same (see Table 4). We thank an anonymous reviewer for this suggestion.

Local–global identity versus nationalism: For this test, Model 1 is the constrained two-factor model where the correlation between local identity and nationalism is fixed to 1 ($\chi^2 (88) = 523.30$, $p < .001$, CFI = .76, GFI = .77, RMSEA = .14). Model 2 is the unconstrained three-factor model where the correlation is released ($\chi^2 (87) = 284.52$, $p < .001$, CFI = .89, GFI = .87, RMSEA = .09). The three-factor model fits significantly better than the two-factor model ($\Delta \chi^2 (1) = 238.78$, $p < .001$), with the other fit indices improved, indicating that local–global identity is conceptually different from nationalism.

Local–global identity versus GCO assimilation: In the two-factor model, the correlation between global identity and GCO assimilation is fixed to 1 ($\chi^2 (52) = 235.80$, $p < .001$, CFI = .81, GFI = .85, RMSEA = .12). The three-factor model releases the constraint ($\chi^2 (51) = 136.97$, $p < .001$, CFI = .91, GFI = .92, RMSEA = .08). The three-factor model fits significantly better than the two-factor model ($\Delta \chi^2 (1) = 98.83$, $p < .001$), with all the other fit indices improved, indicating that local–global identity is conceptually different from GCO assimilation.

Local–global identity versus GCO separation: In the two-factor model, the correlation between local identity and GCO separation is fixed to 1 ($\chi^2 (52) = 251.50$, $p < .001$, CFI = .78, GFI = .85, RMSEA = .12). The three-factor model releases the constraint ($\chi^2 (51) = 153.70$, $p < .001$, CFI = .89, GFI = .91, RMSEA = .09). The three-factor model fits significantly better than the two-factor model ($\Delta \chi^2 (1) = 97.80$, $p < .001$), with all the other fit indices improved, indicating that local–global identity is conceptually different from GCO separation.

5.3.2. Convergent validity

Convergent validity of the local–global identity was supported by the positive correlations between the subscales and other established conceptually related constructs (as shown in Table 4). As predicted, global identity is positively correlated with GCO subscale of assimilation; local identity subscale is positively correlated with GCO subscale for separation and nationalism. Overall, people high on global identity tend to be more positive about substituting global influence for local cultures. In contrast, people high on local identity tend to be more nationalistic and prone to maintaining local culture.

5.4. Discussion

This study provided evidence for the discriminant and convergent validity of the local–global identity construct. The local–global identity scale is significantly correlated but not redundant with measures for nationalism and global consumption orientation.


The purpose of this study is to further establish the convergent validity of the 8-item local–global identity scale by comparing it with conceptually related constructs such as consumer ethnocentrism and global consumption orientation with a different international sample so as to add to the external validity of the results.

6.1. Participants and procedures

One hundred and twenty evening EMBA students from a large Chinese international business university participated in this study for extra course credit. Fifty-one percent of the participants were male, and participants’ ages ranged from 20 to 50 years. The study was translated into Chinese and then translated back into English.

6.2. Measures

Participants completed the 8-item local–global identity and the global consumption orientation GCO (as in study 3) scales. The global and local subscales had reliabilities of .61 and .70, respectively. The reliabilities for the assimilation, separation, hybridization, and lack of interest subscales from the GCO scale were .70, .51, .68, and .63, respectively. The reliability for the consumer ethnocentrism scale was .83. Though the reliabilities are not particularly high, they are similar in magnitude for our proposed 8-item scale and the well-established GCO scale, and thus, the lower magnitudes are perhaps unique to this sample. Detailed correlations between the subscales can be found in Table 5.

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Mean S.D.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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<tr>
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<td>.53</td>
<td>1.00</td>
</tr>
<tr>
<td>GCO separation</td>
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<tr>
<td>Nationalism</td>
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<td>1.26</td>
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<td>−.08</td>
<td>−.24</td>
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</table>

Table 4 Study 3—Correlations.

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<th>2</th>
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<td>Long local</td>
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<tr>
<td>Long global</td>
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<td>.03</td>
</tr>
</tbody>
</table>

Table 5 Study 4—Correlations.
6.3. Results

6.3.1. Convergent validity

If our global and local subscales are valid, then they should predict GCO. More specifically, people high on the global identity subscale should have strong global consumption orientation (assimilation, i.e., substituting global influence for local cultures), and those high on the local identity subscale should have strong local consumption orientation (separation, i.e., maintaining local culture); those high on both the global and local identity subscales will have a hybridization response (i.e., integrating global culture into local culture), and those low on both subscales will show a lack of interest.

For the GCO assimilation measure, the effect of the global identity subscale was significant and positive ($\beta = .28, t = 2.54, p < .05$), whereas the effect of the local identity subscale was significant and negative ($\beta = -.30, t = -2.78, p < .05$). For the GCO separation measure, the effect of the local identity subscale was significant and positive ($\beta = .19, t = 1.99, p < .05$), whereas the effect of the global identity subscale was marginally significant and negative ($\beta = -.18, t = -1.86, p < .07$). For the integration GCO measure, the effect of the global identity subscale was significant and positive ($\beta = .21, t = 2.46, p < .05$), whereas the effect of the local identity subscale was not significant ($\beta = .06, t = .72, p > .45$). For the lack of interest GCO measure, the effect of the global identity subscale was negative though not significant ($\beta = -.16, t = -1.57, p = .12$), whereas the effect of the local identity subscale was significant and negative ($\beta = -.25, t = -2.52, p < .05$). These results clearly show that our proposed 8-item scale is conceptually consistent with the major theories in the globalization literature.

6.3.2. Discriminant validity: local identity versus consumer ethnocentrism

Following Anderson and Gerbing’s (1988) approach to discriminant validity, we conducted a chi-square difference test between two models. In the two-factor model, the correlation between local identity and consumer ethnocentrism was fixed to 1 ($\chi^2 (52) = 237.40, p < .001$, CFI = .61, GFI = .77, RMSEA = .17). The three-factor model releases the constraint ($\chi^2 (51) = 190.70, p < .001$, CFI = .71, GFI = .80, RMSEA = .15). The three-factor model fits significantly better than the two-factor model ($\Delta \chi^2 (1) = 46.70, p < .001$) with all the other fit indices improved, indicating that local–global identity is conceptually different from consumer ethnocentrism. The relatively low fit indices are partly due to the low reliability of the scales as discussed earlier in the measurement section.

7. Study 5: Comparing the 8-item scale with Zhang and Khare’s 19-item scale—U.K. non-student sample

The purpose of this longitudinal online study is to show that our proposed 8-item scale has reliability comparable to that of the 19-item scale proposed by Zhang and Khare (2009). One hundred eighty one U.K. consumers were recruited via a lottery from a paid online panel company, with additional cash incentives for encouraging longitudinal participation. The response rate was 5%. The participants represented a broad cross-section of consumers. Their ages ranged from 18 to 75, 46% were men, their education levels ranged from completion of high school to graduate degree, family size ranged from 1 to 7, and 77% identified themselves as middle class. None of the participants correctly guessed the purpose of the research.

In time 1 of the study, participants completed either our 8-item scale or Zhang and Khare’s 19-item scale (assigned randomly upon clicking on the survey’s link) and then Shimp and Sharma’s (1987) simplified 6-item consumer ethnocentrism scale.

In time 2, one week later, it was ensured that those who completed the 8-item scale in time 1 were now provided with the 19-item scale, and conversely, those who completed the 19-item scale in time 1 were now provided with the 8-item scale. All participants once again completed the same consumer ethnocentrism scale used in time 1. Following these scales, participants indicated their attitudes toward global and local products. They were first provided with these descriptions of global and local products: “Local products are made with specifications and packaging tailored for local markets. Conversely, a global product has specifications and packaging targeting consumers from around the world. For example, in the cola market, there are local products such as Virgin Cola in U.K., Mecca Cola in France, and Future Cola in China and global products such as Pepsi and Coke Cola”. Participants then provided evaluations (1 = Strongly Disagree, 7 = Strongly Agree) of global (“Global products are attractive” and “I like global products”, $r = .90$) and local (“Local products are attractive” and “I like local products”, $r = .82$) products. The time 1–time 2 order for the 8-item and 19-item scales did not influence the results, and thus, it will not be discussed further. Detailed correlations between the subscales can be found in Table 6.

### Table 6

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Mean</th>
<th>S.D.</th>
<th>1 (CI)</th>
<th>2 (CI)</th>
<th>3 (CI)</th>
<th>4 (CI)</th>
<th>5 (CI)</th>
<th>6 (CI)</th>
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<td></td>
<td></td>
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<tr>
<td>Local identity</td>
<td>5.25</td>
<td>1.11</td>
<td>1.00</td>
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<td></td>
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<tr>
<td>Global identity</td>
<td>4.55</td>
<td>1.10</td>
<td>.16</td>
<td>1.00</td>
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<td>Ethnocentrism</td>
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<td>-.24</td>
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<td>GCO separation</td>
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<td>.48</td>
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<td>GCO hybridization</td>
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<td>-.23</td>
<td>.24</td>
<td>-.57</td>
<td>-.12</td>
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<td>GCO no interest</td>
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<td>1.22</td>
<td>-.33</td>
<td>-.13</td>
<td>.15</td>
<td>-.15</td>
<td>-.07</td>
<td>.15</td>
<td>1.00</td>
</tr>
</tbody>
</table>

7.1. Results

7.1.1. Reliability comparison

The 8-item local and global subscales had significant internal reliabilities ($\alpha_{local} = .86, \alpha_{global} = .86$), which were comparable to those for the 19-item local and global subscales ($\alpha_{local} = .86, \alpha_{global} = .83$). The consumer ethnocentrism scale also had significant internal reliabilities, $\alpha = .92$, in both time 1 and time 2, and these are comparable to other studies in the ethnocentrism literature (Shimp & Sharma, 1987).

7.1.2. Predictive ability comparison

The global subscales from the 8- and 19-item scales significantly predicted attitudes toward global products, $\beta_{8-item} = .37 (p < .0001)$ and $\beta_{19-item} = .46 (p < .0001)$. Furthermore, a t-test ($t = .79, p > .45$) showed that these two beta coefficients are not significantly different, indicating that the two global subscales have comparable predictive ability.

The local subscales from the 8- and 19-item scales significantly predicted attitude toward local products, $\beta_{8-item} = .39 (p < .0001)$ and $\beta_{19-item} = .41 (p < .0001)$. A t-test showed that these two beta coefficients are not significantly different ($t = .19, p > .45$), indicating that the two local subscales have comparable predictive ability.
7.1.3. Convergent validity

Although the wording of the local and global items was somewhat different in the 8-item scale as compared to the matching eight items in the 19-item scale, we still decided to use them for testing time 1–time 2 reliability. We averaged the four time 1 local identity items (depending upon the randomization outcome, either from the 8-item scale or from the analogous items from the 19-item scale) and the four time 2 local identity items (again, depending on which scale was completed in time 1, either from the 8-item scale or from the analogous items from the 19-item scale). The time 1 and time 2 averages of the local subscales created in this manner correlated significantly ($r = .65, p < .05$). The four time 1 and time 2 global identity items were averaged in the same manner and correlated significantly ($r = .69, p < .05$). These results indicate strong convergent reliability over time between these two scales. Recall that in study 2, we have already demonstrated strong time 1–time 2 temporal reliability when only the 8-item scale was administered in both times (from study 2: $r_{\text{Local}} = .81, p < .05$; $r_{\text{Global}} = .89, p < .05$). We note that the time 1–time 2 reliability of the consumer ethnocentrism scale in this study is also strong ($r = .80, p < .05$).

7.2. Discussion

The reliability results for the consumer ethnocentrism scale indicate that our sample is of good quality, as the reliability results are comparable to those in the ethnocentrism literature. Furthermore, this sample is a non-student sample with results similar to those from student samples in our earlier studies. These aspects greatly enhance our confidence in the conclusion that our 8-item scale has comparable scale properties to the 19-item scale while, at the same time, it is more efficient because it has significantly fewer items.

8. Study 6: Predictive validity test

The purpose of this study was to further test the predictive ability of our proposed 8-item scale. If our proposed scale taps into consumers’ chronic global and local identities, then measuring and priming these identities should lead to similar yet independent effects on consumers’ preferences between global and local products. According to social psychological research, this is because any construct can be made accessible either by priming or measuring it. For example, Higgins and McCann (1984) showed that the construct of power status can show its effect either through measuring its chronic aspect (authoritarianism scale) or through priming it (manipulated power status). Confidence in our 8-item scale will be strengthened if it shows similar characteristics.

8.1. Design

A total of 87 undergraduate business students from another large southwestern U.S. university participated in this online study for extra course credit. This study took an identity–primed (local vs. global) × identity-measured (local vs. global) between-subjects design.

8.2. Procedure and measures

When participants clicked on the study’s link, they were randomly assigned to either the global ($n = 42$) or local ($n = 45$) prime conditions. The study was described as having several unrelated parts. In part 1, we adapted Srull and Wyer’s (1980) sentence-scrambling priming-task and asked participants to form meaningful sentences from sets of scrambled words. In the global priming condition, participants completed 15 sentences related to global identity; those in the local priming condition completed 15 sentences related to local identity (Appendix A). In part 2, participants read the descriptions of local and global versions of a palm pilot product (Appendix B) and then completed the dependent variable, priming manipulation check, age, and gender measurement items. In the last part, participants completed the 8-item local–global identity scale.

To provide additional, convergent evidence in this study, we used a relative dependent variable for assessing relative instead of separate evaluations of global and local products as in study 5. Participants were shown descriptions of both the global and local versions of the product in a within-subjects manner (order was randomized) and then asked to respond to three items for the relative dependent variable (averaged, $\alpha = .81$). Item 1 assessed the attractiveness of the two product versions ($1 = $The Local version is more attractive, ..., $7 = $The Global version is more attractive), item 2 assessed likeability ($1 = $The Local version is more likeable, ..., $7 = $The Global version is more likeable), and item 3 assessed usefulness ($1 = $The Local version is more useful, ..., $7 = $The Global version is more useful). A higher dependent measure value indicates that the global product is preferred relatively more to the local product. Although we described both the local and global products in the product evaluation task, this did not distract from the prime’s effect, and its effect was not compromised as the results of the priming manipulation check items show (we thank the Editor for suggesting that we provide such an explanation).

Four items ($1 = $Strongly Disagree, ..., $7 = $Strongly Agree) were used for checking the priming manipulation. Two of the items were for global identity: “At this moment, I mainly identify myself as a global citizen” and “At this moment, I feel I am a global citizen.” The other two items were for local identity: “At this moment, I mainly identify myself as a local citizen” and “At this moment, I feel I am a local citizen.” The manipulation check measure was derived by subtracting the average of the local items ($r = .91, p < .05$) from the average of the global items ($r = .89, p < .05$), with a greater value indicating a more accessible global identity. If the manipulation is successful, the average of this difference score measure would be larger in the global prime than in the local prime condition. Conclusions are similar when the measures are analyzed separately.

With regards to the 8-item local–global identity scale, both the local (averaged, $\alpha = .81$) and global (averaged, $\alpha = .78$) items indicated high reliability. These averages as well as the difference between them (global–local; a higher difference score indicates relatively stronger global identity) were separately used in our analyses. None of the participants correctly deduced the study’s purpose. Detailed correlations between the subscales can be found in Table 7.

8.3. Manipulation check

The manipulation check measure showed that the priming was successful as participants in the local priming condition had relatively more momentarily accessible local identity than participants in the global priming condition ($M_{\text{Global Prime}} = −.11, M_{\text{Local Prime}} = −1.52, t = 2.01, p < .05$).

8.4. Independence of measured identity from primed identity

To examine whether measured identity is unaffected by primed identity, we ran different regressions of the local identity average, global identity average, and their difference score on primed identity (coded as global prime = 1 and local prime = 0). In each regression, the effect of primed identity was not significant ($p > .32$), attesting to the distinctness of primed and measured identities and suggesting that the 8-item local–global identity scale measures a stable chronic trait.

<table>
<thead>
<tr>
<th>Table 7</th>
<th>Study 6—Correlations.</th>
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<tr>
<td></td>
<td>Constructs</td>
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<td>Local identity</td>
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<tr>
<td>2</td>
<td>Global identity</td>
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</tbody>
</table>
8.5. Results

We ran a regression of our relative dependent variable (higher values indicating greater preference for the global product version) on measured identity difference score (mean centered), primed identity (global prime = 1, local prime = 0), and their interaction as independent variables. The overall model \( F(3, 83) = 16.57, p < .05 \) and the two main effects (primed identity: \( F(1, 83) = 4.95, p < .05 \); measured identity: \( F(1, 83) = 39.37, p < .05 \)) were significant, but the two-way interaction was not significant \( F(1, 83) = 1.86, p > .17 \). As we predicted, the significant positive main effect of measured identity difference score \( (\beta = .71) \) indicated that relative preference for the global product version was higher for those with relatively higher chronic global than local identity. Also as predicted, the significant main effect of primed identity indicates that preference for the global product was higher in the global than local prime condition \( (M_{GlobalPrime} = 4.17, M_{LocalPrime} = 3.40) \).

We also ran a second regression (we thank an anonymous reviewer for recommending this model) with the same dependent variable and in which, in place of the measured identity difference score, we used the averages for measured local and global identity. In this model \( F(5, 81) = 10.55, p < .05 \), the independent variables were measured global identity \( (\text{mean centered}; \beta = .61; F(1, 81) = 10.70, p < .05) \), measured local identity \( (\text{mean centered}; \beta = -.82; F(1, 81) = 16.00, p < .05) \), primed identity \( (F(1, 81) = 6.15, p < .05) \), the interaction between measured global identity and primed identity \( (\beta = .07; F(1, 81) = .07, p > .79) \), and the interaction between measured local identity and primed identity \( (\beta = .62; F(1, 81) = 4.41, p < .05) \).

The significant effect of primed identity indicates that relative preference for the global product version was higher in the global than local prime condition \( (M_{GlobalPrime} = 4.17, M_{LocalPrime} = 3.40) \). As expected, the significant and positive main effect of measured global identity indicates that relative preference for the global product version was higher for those with relatively higher chronic global identity and that, because the interaction between measured global identity and primed identity was non-significant, this was true in both the local and global prime conditions. Also as expected, the significant and negative main effect of measured local identity coupled with its significant and positive interaction with primed identity means that relative preference for the global product version was lower for those with relatively higher chronic local identity and that the tendency was stronger in the local than global prime condition.

8.6. Discussion

In study 6, we showed that consumers high on the global identity measure tend to perceive global products as more attractive than local products, and those high on the local identity measure tend to perceive local products as more attractive than global products. Likewise, consumers primed with global identity perceive global products as more attractive than local products, and consumers primed with local identity perceive local products as more attractive than global products. Thus, we found that the local–global identity construct’s effects occur both via measurement and manipulation. Furthermore, this study’s results confirm the predictive validity of our proposed local–global identity scale.

9. General discussion

9.1. Summary and contributions

We constructed a shorter scale to demonstrate the influence of a newly defined identity, consumers’ local–global identity, on consumers’ preference for local versus global products. This is an important area of inquiry given the rapid growth of globalization. Specifically, we showed that participants scoring high on global identity, as measured by our scale, found global products to be more attractive than local products, whereas participants scoring high on local identity scale found local products to be more attractive than global products.

We believe that our results make key contributions to the extant literature. First, although Arnett’s (2002) pioneering research on the psychology of globalization delineates the conceptual framework for a local–global identity, measurement efforts of such an identity have been lacking. We proposed and tested scale items for this identity and believe that this will help to advance the emergent research in this important consumer domain.

Second, we provided improvement over earlier scaling efforts. Zhang and Khare’s (2009) 19-item scale is relatively long and that may restrict its use in practice. Our scale has fewer items (8 versus 19) but with comparable reliability and predictive ability, and therefore, we believe it should be more convenient to use.

Third, the consistency in results between our non-student, international samples and Zhang and Khare’s exclusively U.S. student samples is not only reassuring but also enhances the overall generalizability of their and our findings.

Fourth, our scale testing is more comprehensive than that reported in Zhang and Khare (2009). We show that the local–global identity is related to but also very different from constructs such as consumer ethnocentrism, nationalism, and GCO. Although the conceptual connection between local–global identity and GCO, both newly conceptualized constructs, has been suggested in the literature (Steenkamp & de Jong, 2010), our results provide empirical validation.

9.2. Managerial implications

For new products and positioning changes to existing ones, our results suggest that it is important to consider whether a local or global strategy is more likely to appeal to consumers. As companies enter new markets, they may want their products to be seen as locally rooted if the local identity is dominant, but they may want to highlight that their products reflect global tastes if the global identity is dominant. Our results show that a local or global product positioning strategy may be more effective if marketers situationally enhance their consumers’ local or global identity. A situational enhancement of identity can be achieved through advertising, PR events, and sponsorships among other strategies.

Our results provide implications for segmentation decisions as well. Using information about consumers’ local–global identities, companies can segment consumers as locals or globals and position their products in an identity-consistent manner within each segment. As our research shows, even a slight difference in product description can make local products more appealing to the locals segment (higher local identity score) and global product more appealing to the globals segment (higher global identity score). The results shed light on the viability of market segmentation based on measuring consumers’ local–global identity.

Our results show the possibility of combining local–global segmentation with other perspectives on brand positioning. Alden et al. (1999) suggested that firms can rely on the global consumer culture to position their brands to gain competitive advantage. Our results suggest that such a strategy might be more effective for the globals segment than other segments in general. Combining these two perspectives will make global segmentation and positioning practice more effective.

In addition to segmentation and positioning, knowledge about the extent of consumers’ localness and globalness can be used to provide effective, identity-consistent, marketing communication, be it for personal selling, sales promotions, public relations, advertising, and other components of the communication mix.

While the identity scale we propose can help to build a psychological profile of consumers, marketers may like to know if there are any easier-to-observe and easier-to-measure consumer characteristics (such as income, occupation, etc.) that can be used as proxies for
Appendix A. Study 6—Local versus global identity priming

We are interested in how people form meaningful English sentences. Please form meaningful sentences from the following scrambled words.

<table>
<thead>
<tr>
<th>Local prime condition</th>
<th>Global prime condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Events know I local.</td>
<td>1. Events know I global.</td>
</tr>
<tr>
<td>2. The community local I belong to.</td>
<td>2. The world whole I belong to.</td>
</tr>
<tr>
<td>3. I a citizen am local.</td>
<td>3. I a citizen am global.</td>
</tr>
<tr>
<td>4. Try locally to think I.</td>
<td>4. Try globally to think I.</td>
</tr>
<tr>
<td>5. I a viewpoint local hold a.</td>
<td>5. I viewpoint globally hold a.</td>
</tr>
<tr>
<td>6. Smaller our is community getting.</td>
<td>6. Smaller our is world getting.</td>
</tr>
<tr>
<td>7. World our dissimilar becoming is.</td>
<td>7. World our similar becoming is.</td>
</tr>
<tr>
<td>8. Try to I perspectives local understand.</td>
<td>8. Try to I perspectives global understand.</td>
</tr>
<tr>
<td>10. A localized we in live society.</td>
<td>10. A globalized we in live society.</td>
</tr>
<tr>
<td>11. Village a local in we live.</td>
<td>11. Village a global in we live.</td>
</tr>
<tr>
<td>12. We in process of are localization the.</td>
<td>12. We in process of are globalization the.</td>
</tr>
<tr>
<td>13. The localized is very world.</td>
<td>13. The globalized is very world.</td>
</tr>
<tr>
<td>15. A community local is this.</td>
<td>15. A community global is this.</td>
</tr>
</tbody>
</table>

Appendix B. Study 6 stimuli

Palm Pilot Evaluation

An electronics company is planning to manufacture a palm-held interpersonal telecommunication device (e.g., palm pilot). The product can help consumers like you in the following ways:

Keep up-to-date.

It will synchronize with Outlook email, calendar, contacts, tasks, and notes right out of the box.

Be as organized as you want to be.

Easily manage your schedules, contacts, photos, and videos. Stay ahead of your day by color-coding your events.


Capture life with a built-in camera. Shoot photos and video, download to them to your computer, and share with friends.

The company is deciding whether to offer this device as a GLOBAL or LOCAL product. For the GLOBAL version, it plans to emphasize that the product is produced and marketed for global consumers. Thus, consumers from the U.S. and consumers from other parts of the world will be offered a product with the SAME specifications and packaging.

For the LOCAL version, it plans to emphasize that the product is produced and marketed specifically for the local U.S. market. Thus, U.S. consumers will be offered a version that has UNIQUE specifications and packaging as compared to the version offered to consumers from other parts of the world.

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The young adult cohort in emerging markets: Assessing their glocal cultural identity in a global marketplace

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ABSTRACT

Multinational firms perceive the young adult cohort in emerging markets as a relatively homogeneous segment that welcomes global brands and facilitates the entrance of these brands into emerging markets. Research suggests, however, that young adults are a more heterogeneous cohort in which individuals develop a glocal cultural identity that reflects their beliefs about both global phenomena and local culture. Our goal is to evaluate the glocal cultural identity of the young adult cohort based on three global–local identity beliefs (belief in global citizenship through global brands, nationalism, and consumer ethnocentrism) in the emerging markets of Russia (Studies 1 and 2) and Brazil (Study 2). We further assess the consumption practices of the glocal cultural identity segments in relation to global and local brands. Results across the two studies indicate three distinct segments, two of which, the Glocally-engaged and the Nationally-engaged, are consistent across countries. A third idiosyncratic segment emerged in each country, the Unengaged in Russia and the Globally-engaged in Brazil. The most viable segments for multinational firms are the Globally-engaged and the Glocally-engaged; these segments have an identity that is grounded in both global and local cultures and respond favorably to both global and local brands. Nationally-engaged consumers have a more localized identity; they are a more challenging target for firms offering only global brands. The Unengaged segment has weak global–local identity beliefs and low involvement with both global and local consumption practices.

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1. Introduction

The burgeoning young adult cohort is an attractive segment for multinational firms across the globe, particularly in emerging markets (Douglas & Craig, 1997, 2006; Kjeldgaard & Askegaard, 2006). This cohort has been characterized as innovative, open to trying new brands, and conscious of their identity (Lambert-Pandraud & Quelch, & Taylor, 2004; Zhou, Yang, & Hui, 2010). Some researchers argue that young adults are “global” in their identities and are at the forefront of globalization (Schlegel, 2001). Indeed, this global orientation is particularly attractive to multinational firms and global brands that frequently treat this cohort as homogenized and globally-oriented (Askegaard, 2006; Hannerz, 2000). Consumer culture research, however, documents that, although consumers look to, integrate, and react to global consumer culture symbols and signs, they do so in relation to their local cultural discourses (Akaka & Alden, 2010; Ger & Belk, 1996; Hung, Li, & Belk, 2007; Kjeldgaard & Askegaard, 2006); that is, consumers “embrace both the Lexus and the olive tree” (van Ittersum & Wong, 2010, p. 107).

In this research, we draw upon work in cultural identity theory to further explore glocal cultural identity. Cultural identity is defined as “a broad range of beliefs and behaviors that one shares with members of one’s community” (Jensen, 2003, p. 190; Berry, 2001). As globalization has evolved, we now consider community in relation to one’s global and local cultural milieu. Thus, we define glocal cultural identity as the coexistence of a broad range of beliefs and behaviors embedded to varying degrees in both local and global discourses. Because global and local orientations can conflict, an individual’s glocal cultural identity may “account for the different and even opposing demands resulting from the processes of globalization and localization” (Hermans & Dimaggio, 2007, p. 32).

As we seek to understand glocal cultural identity, we recognize three forces at play: (1) globalization and localization coexist and fuel each other (Akaka & Alden, 2010; Hermans & Dimaggio, 2007; Robertson, 1995); (2) individuals reflexively combine local and global identity markers in constructing their glocal cultural identity (Dong & Tian, 2009; Mazzarella, 2004; Varman & Belk, 2009; Zhao & Belk, 2008); and (3) brands constitute a key part of...
cultural identity (Askegaard, 2006; Kjeldgaard & Askegaard, 2006; Kjeldgaard & Østberg, 2007). Specifically in contextualizing glocal cultural identity, we focus on one belief that reflects the influence of globalization, i.e., the belief in global citizenship through global brands (Steenkamp, Batra, & Alden, 2003; Strizhakova, Coulter, & Price, 2008a). This belief embodies the embracing of both global culture and global brands as symbols of the global consumer culture. We also examine two beliefs that reflect dialogical influences of localization: nationalism (Dong & Tian, 2009; Douglas & Craig, 2011; Varman & Belk, 2009) and consumer ethnocentrism (Shimp & Sharma, 1987). Consistent with how national identity has been conceptualized in past research (Keilor, Hult, Erfmfeyr, & Babakus, 1996), nationalism reflects the salience of one’s nation and local culture, and ethnocentrism reflects preferences for locally-produced brands and products.

Our work focuses on the young adult cohort within which the glocal cultural identity is particularly prominent. This cohort is less settled in their identity and more open to sharing varied beliefs and behavioral practices with certain global and local cultural communities (Jensen, 2003; 2011; Kjeldgaard & Askegaard, 2006; Mazzarella, 2003). Specifically, we use cluster analysis to profile individuals on their glocal cultural identity as an integration of their beliefs about global citizenship through global brands, nationalism, and consumer ethnocentrism. Next, in relation to these profiles, we assess the following specific consumer branding practices: 1) consumer involvement with global and local brands, 2) use of global and local brands as quality and self-identity signals, and 3) purchases of global and local brands. We focus on the emerging markets of Russia and Brazil (Study 1 in Russia in 2009; Study 2 in Russia and Brazil in 2010).

Our work makes several important contributions to research on cultural identity and consumption beliefs and practices, with implications for branding, global and local brands, and brand management. First, we contribute to current theory on glocal cultural identity (Ger & Belk, 1996; Jensen, 2003, 2011; Kjeldgaard & Askegaard, 2006, Varman & Belk, 2009) by considering the theory’s grounding in three global–local identity beliefs, including one global cultural belief (belief in global citizenship through global brands) and two local cultural beliefs (nationalism and consumer ethnocentrism). Therefore, we extend the previous research that developed measures of either global or national identity dimensions (Der-Karabetian & Ruiz, 1997; Keilor et al., 1996; Zhang & Khare, 2009) to incorporate a profiling approach as an alternative strategy to understanding glocal cultural identity. Second, we further examine glocal cultural identity profiles in relation to branding practices. Specifically, we extend prior research on consumer attitudes toward global and local products (Steenkamp & de Jong, 2010) to examine involvement with brands, consumers’ use of brands as signals of quality and self-identity, and purchases of global and local brands. Third, our focus is on the young adult cohort in the emerging markets of post-socialist Russia and post-colonial Brazil; these young adults are an attractive target for multinational firms and global brands but have received little research attention (Douglas & Craig, 2011). Our research draws upon work on globalization and cultural identity in consumer culture theory and in quantitative marketing paradigms and consequently helps integrate and bridge these two perspectives. Collectively, our findings suggest that multinational and local companies need to be cognizant of the complex and changing nature of young adults’ glocal cultural identity in emerging markets, as they offer promising opportunities for potential growth (Burgess & Steenkamp, 2006; Wilson & Purushothaman, 2003).

In the following section, we discuss our conceptual framework, focusing on the cultural identity formation among young adults in the age of globalization, conceptualizing glocal cultural identity, and linking this identity to branding practices. Next, we provide an overview of our research in Russia and Brazil, including a brief discussion of the socio-historical differences and similarities in these two countries that are pertinent to the formation of the glocal cultural identity. We then describe our two studies and findings in detail and conclude with a discussion, the managerial implications, and future research opportunities.

2. Conceptual framework

2.1. Glocal cultural identity formation in the age of globalization

A challenge faced by young adults in the age of globalization is making decisions about how their worldview beliefs and behavioral practices relate to global and local cultures—that is, their glocal cultural identity (Berry, 2001; Jensen, 2003, 2011). We recognize and discuss three forces at play in how young adults in the modern world form their glocal cultural identity: (1) the co-dependency of globalization and localization, (2) dialogical use of global and local identity markers, and (3) brands as key components of glocal cultural identity.

First, the interplay between globalization and localization is at the core of glocal cultural identity formation. Cultural identity is often framed as a tension or a competing choice between global and local identity, but there is increasing recognition that both identities are intertwined in mediated, complex, nuanced conversations with each other (Dong & Tian, 2009; Mazzarella, 2004; Varman & Belk, 2009; Zhao & Belk, 2008). Paradoxically, rather than having a homogenizing effect, globalization has fueled a boom in localization (Hung et al., 2007), implying that globalization and localization are unintelligible except in reference to each other. Hence, the concept of “glocalization” emerges where “both coexist and fuel each other in dialectical ways” (Hermans & Dimaggio, 2007: p. 33; Robertson, 1995). In other words, that which is defined as global in a given culture is contingent upon what is defined as local, and vice versa (Alaka & Alden, 2010).

Second, there is an evolving discussion about cultural identity formation in the context of globalization. Arnett (2002) posited that young people create a bicultural, or hybrid, identity successfully combining elements of global and local culture. Hermans and Dimaggio (2007) extended this thinking, positing a dialogical perspective where globalization challenges young adults to extend their cultural identity beyond the reach of traditional structures. This extension precipitates uncertainty and motivates the young adults to maintain, and even expand, their local values in pursuit of a stable identity. The authors further contend that globalization, as a key element of cultural identity, can also fuel nationalism, because it is an institutionalized identity marker in times of rapid change and uncertain futures. Hence, young adults may embrace globalization fearlessly (much as other generations abandoned home and family and sought out new frontiers), or successfully combine traditional identity markers such as nationalism with a global identity (balancing extension with security and familiarity), or may engage in defensive localization fueled by the fear of the encroaching others (Kinnvall, 2004). In the latter case, defensive localization can take the relatively mild marketplace form of ethnocentrism or can escalate into more extreme forms such as terrorism.

Third, branded products, because of their communicative, symbolic, and social functions (Kjeldgaard & Østberg, 2007; Merz, He, & Alden, 2008; Strizhakova, Coulter, & Price, 2008b), are embedded in cultural production systems and mediated through national and global technologies. Branded products constitute a key part of cultural identity (Askegaard, 2006). Hence, changes in brands' occurrence as a result of globalization are likely to influence the cultural identity developments of young adults (Hermans & Kempen, 1998; Jensen, 2011; Manning, 2010). Specifically, “brands can align themselves with respect to social imaginaries such as the nation by situating themselves within local or global trajectories of circulation...or they can gesture to diasporic, aspirational, or exotic elsewhere on the horizons of imaginative geographies of alterity” (Manning, 2010, p. 39; Mazzarella, 2003; Özkan & Foster, 2005). For example, many
recent studies show how strategies of localization situate brands within “the imagined cultural specificities of cities, regions, and nations,” while at the same time “positioning themselves as aspirational global brands” (Manning, 2010, p. 39; Manning & Uplisashvili, 2007; Vann, 2005; Wang, 2007).

2.2. Conceptualizing glocal cultural identity

Cultural identity among young adults is integrated with branding discourses, is fueled by globalization-localization processes and reflects the dialogical use of global and local identity markers, such as global and local beliefs. We conceptualize glocal cultural identity as defined by varying degrees of three global-local identity beliefs: global citizenship through global brands, nationalism, and consumer ethnocentrism. Research has emphasized that global brands are positioned as a means to express one’s global belongingness (Alden, Steenkamp, & Batra, 1999, 2006; Holt et al., 2004; Steenkamp et al., 2003); and Strizhakova et al. (2008a) have argued that consumers who believe in global citizenship through global brands embrace global brands as a way of expressing engagement with the world. Hence, global citizenship through global brands is a belief reflective of the global dimension of glocal cultural identity. In contrast, nationalism and consumer ethnocentrism are beliefs reflective of the local dimension of glocal cultural identity. Nationalism, defined as positive feelings toward one’s national identification, national pride and national respect (Crane, 1999; Keilior et al., 1996), is escalating and is fueled by globalization, particularly in the emerging BRIC markets (Douglas & Craig, 2011). Moreover, beliefs about global brands also evoke feelings and thoughts about local brands and locally-made products. Consumer ethnocentrism, in particular, questions the “appropriateness, indeed morality, of purchasing foreign-made products” (Shimp & Sharma, 1987, p. 280) and speaks in support of locally-made goods. Hence, both nationalism and consumer ethnocentrism resonate with the local dimension of glocal cultural identity; the former is a broader belief evoked in response to the consumers’ evaluation of their citizenship, whereas the latter is a consumption-based belief evoked in response to global brands and foreign-made products.

The choice of these three global-local identity beliefs is grounded in three forces that we identify as vital to the formation of glocal cultural identity among young adults. First, globalization and localization are co-dependent. While global brands promote discourses of global citizenship and culture in their campaigns, they simultaneously fuel the growth of national pride and support for local manufacturers (Douglas & Craig, 2011). Second, young adults, who are particularly open to media and other cultural influences, are challenged to dialogically combine these conflicting global and local beliefs when forming their glocal cultural identity. For example, Chinese and Brazilian youth paradoxically combine nationalism with a desire for “the American life” (Fong, 2004; Troiano, 1997). Third, brands play a key role in young adults’ glocal cultural identity. Belief in global citizenship through global brands provides consumer belonging and association with the global culture projected by the global brands; consumer ethnocentrism counterbalances this striving for global belonging with a moral obligation to support local manufacturers. Hence, we argue that three global-local identity beliefs regarding global citizenship through global brands, one’s national pride, and the morality of purchasing foreign-made products contribute to the formation of glocal cultural identity.

2.3. Glocal cultural identity and branding practices

Globalization further challenges young adults by presenting them with an expansive variety of consumption choices. For example, global brands such as Coke and Pepsi are positioned in competition to Buratino (Russia) and Guarana Antarctica (Brazil); similarly, globally marketed Dannon yogurts are on the grocer’s shelf next to local brands in Russia (Azbuka) and Brazil (Batavo). These global and local brands differentiate themselves by signaling varying meanings, such as quality and self-identity (Erdem, Swait, & Valenzuela, 2006; Fischer, Völkner, & Sattler, 2010; Özisomer & Altaras, 2008), and hence, the marketplace is filled with contending appeals from global and local brands. In forming their glocal cultural identity, young adults not only negotiate global and local cultural beliefs, but also negotiate consumption practices, such as those related to brands.

Extant research tends to examine the effects of idiosyncratic beliefs on branding practices. For example, Steenkamp and de Jong (2010) find that young adult consumers who have lower ethnocentric beliefs are likely to embrace a “homogenization response” reflective of their more positive attitudes toward global products. Other researchers show that consumers that hold stronger beliefs in global citizenship through global brands appear to be more attuned to the general branding ideologies, to place greater value on branded products in general (Strizhakova et al., 2008b), and express preferences exclusively for global brands (Holt et al., 2004). In general, consumer ethnocentrism has been linked to foreign brand aversion (e.g., Nijssen & Douglas, 2004; Sharma, 2011) and domestic brand preference (Balabanis & Diamantopoulos, 2004; Supphellen & Rittenburg, 2001). Yet other work, focused specifically on young adult consumers, indicates that ethnocentric young adult consumers may favor global and local brands equally (Kinra, 2006). This research is suggestive of how the dialogical interplay of local and global cultural identity markers is projected in consumer branding practices.

3. Overview of research

Global brand managers striving to succeed in emerging markets need to be aware of the effects of glocal cultural identity on consumer branding practices. In two studies, we investigate glocal cultural identity by profiling young adults on three global-local identity beliefs (global citizenship through global brands, nationalism, and consumer ethnocentrism). We next examine the different glocal cultural identity profiles with regard to: 1) involvement with local and global brands (Coulter, Price, & Feick, 2003), 2) the use of global and local brands as important quality and self-identity signals (Fischer et al., 2010; Strizhakova et al., 2008b; Tsai, 2005), and 3) purchases of global and local brands (Cayla & Eckhardt, 2008; van Ittersum & Wong, 2010). We focus on young adults in Russia and Brazil, two markets of the BRIC group that differ in their cultural institutions and socio-historic development but share some similarities because of globalization.

Historically, two relevant differences emerge in cultural identity formation between Russia and Brazil. First, Russia was a closed economy for almost three-quarters of a century prior to 1991; although branding and marketplace exchanges existed during that time, they were both quite distinct from those in Western countries and other emerging markets, such as Brazil (Cayla & Arnould, 2008; Kravets & Örge, 2010; Manning & Uplisashvili, 2007). Specifically, distinctions between products and brands were, in many cases, blurred under communist rule and, consequently, consumers are still learning to rely on brands as much as they rely on other cues, such as price, place of sale, and product or ingredient information (Coulter et al., 2003; Walker, 2008). Brazil, however, has had an open-market economy with a long history of local branding and consumption practices similar to those in Western countries. Hence, the Russian (in contrast to Brazilian) consumers’ exposure to free-market practices, to a “westernized” consumer culture, and to other variations in cultural ideologies is in its infancy.

The second difference is based in the history of nationalism in Russia and Brazil. Although a multi-ethnic country, Russia has never been a country of immigrants but is instead a state with one dominant ethnic group (similar to many European countries). As a result,
its national identity and nationalism date back to imperial times (Weeks, 1996) and have only been strengthened by globalization. As Russia opens its borders, such deeply-rooted nationalism is also likely to evoke tensions and feelings of nihilism and disengagement within those who do not fit the national identity profile [similar to Josiassen’s (2011) disidentified consumers in the Netherlands] or who do not abide to its historic code. In contrast, Brazil has been a country of immigrants, developing its nationalist sentiment largely in response to ongoing globalization processes. Similar to other countries built on immigration (e.g., the U.S. or Canada), nationalism in Brazil is not embedded within a particular ethnic group, but rather within diverse groups and is, therefore, less likely to result in strong nihilistic tendencies.

Despite these two socio-cultural differences, the two emerging markets share similarities because of ongoing globalization. Globalization has brought greater openness and economic growth to both. Both Brazil and Russia (“Relating to the emerging global middle class”, 2007). Both countries are comparable to the U.S. and other developed countries in their Internet use among young adults, and foreign travel has been steadily increasing (“The holiday experience – what consumers are looking for in a holiday”, 2011). As globalization created grounds for economic growth, it also triggered the growth of nationalistic rhetoric and sentiment, once again demonstrating that globalization and localization fuel each other and evolve in dialogical ways (Akaka & Alden, 2010; Hermans & Dimaggio, 2007; Hermans & Kempen, 1998). Political and business rhetoric, although welcoming of globalization and foreign investing, portrays the BRIC alliance as a powerful counterforce to the U.S. and other developed countries (“Brazilian consumers in 2020: The local setting”; 2011; “In love with Russia”, 2008).

Finally, both formal and informal (“black” market) economies span the global and local brandscapes in Russia and Brazil. The formal market in both countries is composed of multinational and local businesses, selling global (mainly foreign) and local brands. The informal market consists of brands of unidentifiable origins, unbranded products and counterfeits (“Brazil: Growth market of the future”, 2010; “Russia: Growth market for the future”, 2009). Euromonitor’s Global Market Information Database 2009 brand market share data across eight consumer product categories indicate that the average market share of global versus local brands was 48% versus 19% in Russia and 44% versus 20% in Brazil. The remaining 33% in Russia and 36% in Brazil were attributed to “others,” a category that combines brands and products with market shares of less than 1%, many of which may stem from the informal marketplace.

4. Study 1

In Study 1, we use cluster analysis to examine the glocal cultural identity of young adults in Russia by segmenting them on three global–local identity beliefs: belief in global citizenship through global brands, nationalism, and consumer ethnocentrism. Once segmented, we examine each segment’s profile with regard to its involvement with global and local brands and its use of global and local brands as signals of quality and self-identity.

4.1. Sample and procedure

Undergraduate students from a public university in far-eastern Russia (n = 250, Mage = 19.21, SD = 1.65, 64% females) participated in our study for extra-credit in the early spring of 2009. Approximately one-third of the students worked part-time and approximately 80% had easy access to the Internet. Approximately 43% of the participants had never traveled abroad, 53% had traveled only to neighboring China, and only 4% had traveled to more than one foreign country.

Our survey was written in English and then was translated into Russian by a native speaker and back-translated into English by another Russian native-speaker. Participants completed a pencil-and-paper survey that included measures of our three global–local identity beliefs: belief in global citizenship through global brands, consumer ethnocentrism, nationalism, consumer involvement with brands, use of global and local brands as quality and self-identity signals, and demographic variables. As a point of reference, at the beginning of the survey, we provided definitions of global and local brands (Özsömer & Altaras, 2008; Schuiling & Kapferer, 2004). We defined global brands as those brands distributed and promoted under the same brand name in more than one country and provided examples of regional or national brands of soda (Monasturskaya), car (Volga), beer (Baltika), and supermarket (Plus). To ensure that participants were distinguishing between global and local brands, they were asked to list examples of one global and one local brand for five product categories (TV sets, mineral water, beer, ice-cream and banks) that have both global and local brands in the Russian market. Participants had a clear understanding of global versus local brands, as 100% were correctly identified.

4.2. Measurement

We used previously developed (seven-point item) scales to measure the three global–local identity beliefs: global citizenship through global brands (three items, Strizhakova et al., 2008a), nationalism (five items, Keillor, Hult, Errffmeyer, & Babakus, 1996), and consumer ethnocentrism (five items, Shimp & Sharma, 1987). To measure consumer use of global and local brands as signals of quality and self-identity, we used three items each from the quality and self-identity dimensions of Strizhakova et al.’s (2008b) scale where branded products were referenced as either “global” or “local” brands. Finally, we adapted six items (Laurent & Kapferer, 1985) to measure consumer involvement with global (local) brands. Scale items, factor loadings, fit indices, means, and reliabilities are presented in Table 1.

We followed Fornell and Larcker’s (1981) procedures to assess the convergent and discriminant validity of all measures. A minimal convergent validity of .70 is recommended. The minimal composite reliability of our measures is .80; thus, our measures exhibit sufficient convergent validity. Second, the average variance extracted for our measures was above .50. All between-construct correlations were below unity (largest r = .71), and all within-construct correlations were greater than the between-construct correlations. Therefore, all of our measures exhibited sufficient convergent and discriminant validity (see Table 2).

4.3. Results

We have conceptualized glocal cultural identity on the basis of three global–local identity beliefs: belief in global citizenship through global brands, nationalism, and consumer ethnocentrism. The young adult sample in Russia expresses a significantly stronger level of nationalism (M = 4.78) than consumer ethnocentrism (M = 3.56; t(249) = 12.59, p < .001) and belief in global citizenship through global brands (M = 3.41; t(249) = 12.35, p < .001); we find no significant differences in the levels of belief in global citizenship through global brands and consumer ethnocentrism (t(249) = 1.70, p > .05).

To segment our participants on glocal cultural identity, we began with a hierarchical cluster analysis using the average linkage method. The resulting dendogram indicated the presence of three distinct clusters. We proceeded by running a K-means cluster analysis with three clusters, and found that the clusters differed significantly on...
our three global–local identity beliefs (Wilks’ λ = .16, F = 122.87, p < .001). We first discuss each cluster configuration and then report on the differences in the levels of the global–local identity beliefs across the clusters (see Table 3). The largest cluster with 41% of participants is the Glocally-engaged, who have similar moderate (on a seven-point scale) levels of nationalism (.495), global citizenship

Table 1
Study 1 and Study 2: Construct indicators, factor loadings, t-values, means, and reliabilities.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Study 1</th>
<th>Study 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Russia n = 250</td>
<td>Russia n = 308</td>
</tr>
<tr>
<td>Global citizenship through global brands (mean, Cronbach’s alpha)</td>
<td>(3.41, .90)</td>
<td>(3.43, .91)</td>
</tr>
<tr>
<td>Buying global brands makes me feel like a citizen of the world.</td>
<td>.88</td>
<td>.85</td>
</tr>
<tr>
<td>Purchasing global brands makes me feel part of something bigger.</td>
<td>.92</td>
<td>.92</td>
</tr>
<tr>
<td>Buying global brands gives me a sense of belonging to the global marketplace.</td>
<td>.82</td>
<td>.88</td>
</tr>
<tr>
<td>Consumer ethnocentrism (mean, Cronbach’s alpha)</td>
<td>(3.36, .85)</td>
<td>(3.38, .86)</td>
</tr>
<tr>
<td>Russian* products, first, last and foremost.</td>
<td>.56</td>
<td>.51</td>
</tr>
<tr>
<td>Purchasing foreign-made products is not Russian.</td>
<td>.76</td>
<td>.76</td>
</tr>
<tr>
<td>It is not right to purchase foreign-made products because it puts fellow Russians out of jobs.</td>
<td>.83</td>
<td>.82</td>
</tr>
<tr>
<td>We should purchase products manufactured in Russia instead of letting other countries get rich off of us.</td>
<td>.76</td>
<td>.79</td>
</tr>
<tr>
<td>Russian consumers who purchase products made in other countries are responsible for putting their fellow Russians out of work.</td>
<td>.78</td>
<td>.82</td>
</tr>
<tr>
<td>Nationalism (mean, Cronbach’s alpha)</td>
<td>(4.78, .89)</td>
<td>(4.77, .92)</td>
</tr>
<tr>
<td>Russia has a strong historical heritage.</td>
<td>.80</td>
<td>.82</td>
</tr>
<tr>
<td>Russian citizens are proud of their nationality.</td>
<td>.79</td>
<td>.84</td>
</tr>
<tr>
<td>One of the things that distinguishes Russia from other countries is its traditions and customs.</td>
<td>.85</td>
<td>.85</td>
</tr>
<tr>
<td>Consumer use of global brands as quality signals (mean, Cronbach’s alpha)</td>
<td>(4.15, .79)</td>
<td>(4.48, .87)</td>
</tr>
<tr>
<td>A global brand name tells me a great deal about the quality of a product.</td>
<td>.68</td>
<td>.79</td>
</tr>
<tr>
<td>A global brand name is an important source of information about the durability and reliability of the product.</td>
<td>.77</td>
<td>.85</td>
</tr>
<tr>
<td>I can tell a lot about a product’s quality from the global brand name.</td>
<td>.81</td>
<td>.83</td>
</tr>
<tr>
<td>Consumer use of global brands as self-identity signal (mean, Cronbach’s alpha)</td>
<td>(3.70, .91)</td>
<td>(3.86, .88)</td>
</tr>
<tr>
<td>My choice of global brands says something about me as a person.</td>
<td>.80</td>
<td>.84</td>
</tr>
<tr>
<td>I choose global brands that help to express my identity to others.</td>
<td>.81</td>
<td>.84</td>
</tr>
<tr>
<td>Global brands that I use communicate important information about the type of person I am as a person.</td>
<td>.76</td>
<td>.87</td>
</tr>
<tr>
<td>Involvement with local brands (mean, Cronbach’s alpha)</td>
<td>(4.17, .83)</td>
<td></td>
</tr>
<tr>
<td>Global brands play a prominent role in my daily life.</td>
<td>.68</td>
<td></td>
</tr>
<tr>
<td>I can name global brands in many product categories.</td>
<td>.64</td>
<td></td>
</tr>
<tr>
<td>Global brands are important to me.</td>
<td>.72</td>
<td></td>
</tr>
<tr>
<td>I am knowledgeable about different global brands in many product categories.</td>
<td>.70</td>
<td></td>
</tr>
<tr>
<td>Global brands interest me.</td>
<td>.70</td>
<td></td>
</tr>
<tr>
<td>I am familiar with many global brands.</td>
<td>.68</td>
<td></td>
</tr>
<tr>
<td>Consumer use of local brands as quality signals (mean, Cronbach’s alpha)</td>
<td>(3.84, .84)</td>
<td>(4.07, .82)</td>
</tr>
<tr>
<td>A local brand name tells me a great deal about the quality of a product.</td>
<td>.71</td>
<td>.77</td>
</tr>
<tr>
<td>A local brand name is an important source of information about the durability and reliability of the product.</td>
<td>.81</td>
<td>.76</td>
</tr>
<tr>
<td>I can tell a lot about a product’s quality from the local brand name.</td>
<td>.78</td>
<td>.78</td>
</tr>
<tr>
<td>Consumer use of local brands as self-identity signal (mean, Cronbach’s alpha)</td>
<td>(3.42, .88)</td>
<td>(3.49, .89)</td>
</tr>
<tr>
<td>My choice of local brands says something about me as a person.</td>
<td>.70</td>
<td>.78</td>
</tr>
<tr>
<td>I choose local brands that help to express my identity to others.</td>
<td>.87</td>
<td>.87</td>
</tr>
<tr>
<td>Local brands I use communicate important information about the type of person I am as a person.</td>
<td>.82</td>
<td>.90</td>
</tr>
<tr>
<td>Involvement with local brands (mean, Cronbach’s alpha)</td>
<td>(3.89, .89)</td>
<td></td>
</tr>
<tr>
<td>Local brands play a prominent role in my daily life.</td>
<td>.64</td>
<td></td>
</tr>
<tr>
<td>I can name local brands in many product categories.</td>
<td>.71</td>
<td></td>
</tr>
<tr>
<td>Local brands are important to me.</td>
<td>.69</td>
<td></td>
</tr>
<tr>
<td>I am knowledgeable about different local brands in many product categories.</td>
<td>.74</td>
<td></td>
</tr>
<tr>
<td>Local brands interest me.</td>
<td>.73</td>
<td></td>
</tr>
<tr>
<td>I am familiar with many local brands.</td>
<td>.70</td>
<td></td>
</tr>
<tr>
<td>Fit indices:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>χ² (df)</td>
<td>1037 (558)</td>
<td>866.81 (462)</td>
</tr>
<tr>
<td>CFI</td>
<td>.93</td>
<td>.96</td>
</tr>
<tr>
<td>TLI</td>
<td>.92</td>
<td>.94</td>
</tr>
<tr>
<td>RMSEA</td>
<td>&lt;.06</td>
<td>&lt;.04</td>
</tr>
</tbody>
</table>

Note: *References to “Russian” and “Russia” were substituted with “Brazilian” and “Brazil” in Study 2 for Brazil.

Table 2
Study 1: Assessment of convergent and discriminant validity: composite reliability, average variance extracted, and Pearson r correlations (squared Pearson r correlations).

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Composite reliability</th>
<th>Average variance</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Global citizenship through global brands</td>
<td>.91</td>
<td>.76</td>
<td>.55</td>
<td>.30</td>
<td>.29</td>
<td>.50</td>
<td>.54</td>
<td>.29</td>
<td>.55</td>
<td>.30</td>
<td>.51</td>
</tr>
<tr>
<td>2. Consumer ethnocentrism</td>
<td>.86</td>
<td>.55</td>
<td>.31</td>
<td>.10</td>
<td>.30</td>
<td>.49</td>
<td>.38</td>
<td>.14</td>
<td>.30</td>
<td>.09</td>
<td>.32</td>
</tr>
<tr>
<td>3. Nationalism</td>
<td>.89</td>
<td>.68</td>
<td>.19</td>
<td>.04</td>
<td>.04</td>
<td>.00</td>
<td>.30</td>
<td>.09</td>
<td>.28</td>
<td>.08</td>
<td>.13</td>
</tr>
<tr>
<td>4. Global brands as quality signals</td>
<td>.80</td>
<td>.57</td>
<td>.67</td>
<td>.49</td>
<td>.60</td>
<td>.36</td>
<td>.45</td>
<td>.20</td>
<td>.35</td>
<td>.12</td>
<td>.42</td>
</tr>
<tr>
<td>5. Global brands as self-identity signals</td>
<td>.84</td>
<td>.63</td>
<td>.71</td>
<td>.50</td>
<td>.48</td>
<td>.23</td>
<td>.50</td>
<td>.25</td>
<td>.49</td>
<td>.24</td>
<td>.49</td>
</tr>
<tr>
<td>6. Involvement with global brands</td>
<td>.83</td>
<td>.69</td>
<td>.48</td>
<td>.23</td>
<td>.49</td>
<td>.24</td>
<td>.60</td>
<td>.36</td>
<td>.60</td>
<td>.36</td>
<td>.60</td>
</tr>
<tr>
<td>7. Local brands as quality signals</td>
<td>.81</td>
<td>.59</td>
<td>.69</td>
<td>.48</td>
<td>.61</td>
<td>.37</td>
<td>.51</td>
<td>.25</td>
<td>.51</td>
<td>.25</td>
<td>.51</td>
</tr>
<tr>
<td>8. Local brands as self-identity signals</td>
<td>.84</td>
<td>.64</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. Involvement with local brands</td>
<td>.85</td>
<td>.69</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
through global brands, (4.69), and consumer ethnocentrism (4.35). In contrast, the Nationally-engaged, representing 33% of participants, express strong nationalism (5.99) and low levels of consumer ethnocentrism (3.32) and global citizenship through global brands (2.76). The smallest cluster, the Unengaged (26% of participants), indicates low levels (<3.0) on each of the three global–local identity beliefs.

Univariate ANOVA tests across the clusters reveal significant differences for each of the global–local identity beliefs (see Table 3 for means and F-tests). Specifically, the Glocally-engaged (in contrast to the other two clusters) have the strongest belief in global citizenship through global brands and the strongest consumer ethnocentrism, whereas the Nationally-engaged have the strongest nationalistic beliefs; the Unengaged express the weakest level on each of the global–local identity beliefs. Finally, we find no significant differences across the clusters on Internet access, travel abroad, and gender; however, there was a difference on age ($F(2, 247) = 14.66, p < .001$) with the Nationally-engaged slightly older ($M = 19.99$) than the Unengaged ($M = 18.74$) and the Glocally-engaged ($M = 18.87$).

We next examined the three clusters with regard to their involvement with global and local brands and their use of global and local brands as signals of quality and self-identity. A MANOVA with local and global brand involvement as the dependent variables was significant (Wilks’s $\lambda = .83, F = 12.38, p < .001$), and the univariate ANOVAs were also significant (see Table 4). As might be expected, the post-hoc Scheffé tests ($p < .001$) reveal that the Glocally-engaged are significantly more involved with both global and local brands than either of the other clusters, and the Nationally-engaged are more involved with local brands than the Unengaged. A MANOVA with consumer

| Table 3 |
| Study 1 and Study 2: Cluster analysis results by country. |

<table>
<thead>
<tr>
<th>Glocal cultural identity clusters</th>
<th>Overall mean</th>
<th>$F$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Globally-engaged</td>
<td>Glocally-engaged</td>
<td>Nationally-engaged</td>
</tr>
<tr>
<td><strong>Russia: Study 1</strong></td>
<td>NA</td>
<td>n = 102 (41%)</td>
</tr>
<tr>
<td>Global citizenship through global brands</td>
<td>4.69a</td>
<td>2.76a</td>
</tr>
<tr>
<td>Nationalism</td>
<td>4.95a</td>
<td>5.99a</td>
</tr>
<tr>
<td>Consumer ethnocentrism</td>
<td>4.35a</td>
<td>3.32a</td>
</tr>
<tr>
<td><strong>Russia: Study 2</strong></td>
<td>NA</td>
<td>n = 155 (50%)</td>
</tr>
<tr>
<td>Global citizenship through global brands</td>
<td>4.61a</td>
<td>1.95a</td>
</tr>
<tr>
<td>Nationalism</td>
<td>5.26a</td>
<td>5.49a</td>
</tr>
<tr>
<td>Consumer ethnocentrism</td>
<td>4.15a</td>
<td>2.88a</td>
</tr>
<tr>
<td><strong>Brazil: Study 2</strong></td>
<td>n = 58 (31%)</td>
<td>n = 64 (34%)</td>
</tr>
<tr>
<td>Global citizenship through global brands</td>
<td>5.08a</td>
<td>4.13a</td>
</tr>
<tr>
<td>Nationalism</td>
<td>5.17a</td>
<td>5.34b</td>
</tr>
<tr>
<td>Consumer ethnocentrism</td>
<td>2.14a</td>
<td>4.75ab</td>
</tr>
</tbody>
</table>

*Within cluster t-tests of consumer beliefs indicate significant differences between the beliefs within each cluster (<.05), with the exceptions in Study 2 in Russia for the Unengaged and in Brazil for the Glocally-engaged.

The same letter superscript indicates significant ($p < .05$) differences between clusters on a given variable. Different letter superscripts indicate no significant differences between clusters on a given variable. NA indicates that the cluster was not observed in a given country.

** p < .01.

*** p < .001.

| Table 4 |
| Study 1 and Study 2: Glocal cultural identity clusters and global and local brand practices by country. |

<table>
<thead>
<tr>
<th>Glocal cultural identity clusters</th>
<th>F-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Globally-engaged</td>
<td>Glocally-engaged</td>
</tr>
<tr>
<td>Study 1: Russia</td>
<td>NA</td>
</tr>
<tr>
<td>Involvement with global brands</td>
<td>4.37a</td>
</tr>
<tr>
<td>Involvement with local brands</td>
<td>4.63ab</td>
</tr>
<tr>
<td>Use of global brands as signals of quality</td>
<td>4.34ab</td>
</tr>
<tr>
<td>Use of local brands as signals of quality</td>
<td>4.30a</td>
</tr>
<tr>
<td>Use of local brands as signals of self-identity</td>
<td>4.11ab</td>
</tr>
<tr>
<td>Study 2: Russia</td>
<td>NA</td>
</tr>
<tr>
<td>Percentage of global brands purchased</td>
<td>17.4a</td>
</tr>
<tr>
<td>Percentage of local brands purchased</td>
<td>32.4a</td>
</tr>
<tr>
<td>Use of global brands as signals of quality</td>
<td>4.79ab</td>
</tr>
<tr>
<td>Use of local brands as signals of quality</td>
<td>4.49ab</td>
</tr>
<tr>
<td>Use of local brands as signals of self-identity</td>
<td>4.44a</td>
</tr>
<tr>
<td>Study 2: Brazil</td>
<td>NA</td>
</tr>
<tr>
<td>Percentage of global brands purchased</td>
<td>30.1</td>
</tr>
<tr>
<td>Percentage of local brands purchased</td>
<td>19.4a</td>
</tr>
<tr>
<td>Use of global brands as signals of quality</td>
<td>5.22a</td>
</tr>
<tr>
<td>Use of local brands as signals of quality</td>
<td>4.27b</td>
</tr>
<tr>
<td>Use of local brands as signals of self-identity</td>
<td>5.38a</td>
</tr>
<tr>
<td>Use of local brands as signals of quality</td>
<td>4.18a</td>
</tr>
</tbody>
</table>

The same letter superscript indicates significant ($p < .05$) differences between clusters on a given variable.

** p < .01.

*** p < .001.
use of global and local brands as signals of quality and self-identity as the dependent variables was also significant (Wilks’ $\lambda = .71$, $F = 11.34$, $p < .001$). The post-hoc Scheffé tests indicate a similar pattern of results; the Glocally-engaged are significantly more likely to use global and local brands as signals of quality and self-identity than either the Nationally-engaged or the Unengaged. The latter two segments are undifferentiated on their use of global brands as signals of quality and self-identity; however, with regard to local brands, the Nationally-engaged (vs. the Unengaged) are significantly more likely to use local brands as signals of quality.

To summarize, the Study 1 findings offer initial support for the existence of global cultural identity segments among young adult consumers in Russia based on three global–local identity beliefs. Across the segments, differences exist in their levels of involvement with global and local brands, as well as in their use of local and global brands as signals of quality and self-identity.

5. Study 2

We conducted Study 2 with young adult consumers from Russia and Brazil in the spring of 2010. Our goals were three-fold: 1) to determine if similar local cultural identity segments would be evident in Russia within a one-year time horizon, 2) to compare the glocal cultural identity segmentation of the young adults in Russia to those in Brazil, and 3) to examine the effects of the glocal cultural identity on purchases of global and local brands in ten product categories and to examine consumer use of local and global brand signals of quality and self-identity.

5.1. Sample, procedure and measures

Undergraduate students from far-eastern Russia, who did not participate in Study 1 ($n = 308$; $M_{\text{age}} = 19.85$, $SD = 1.87$; 55% females), and from north eastern Brazil ($n = 186$; $M_{\text{age}} = 23.22$, $SD = 3.41$; 65% females) participated in the study; a lottery for monetary prizes was offered. All participants were full-time students; yet their employment status varied across country samples ($\chi^2 (3, 494) = 299.61$, $p < .001$; not employed (Russia = 78%; Brazil = 31%), employed part-time (Russia = 17%; Brazil = 43%); and employed full-time (Russia = 5%; Brazil = 26%). Approximately 53% of participants in Russia and 85% in Brazil had never traveled abroad; the vast majority of the remaining participants had traveled to the neighboring country (China and Argentina, correspondingly), and less than 1% of the participants from each country had traveled to more than one foreign country. About 88% in Russia and 80% in Brazil reported using the Internet at home, school or work.

We followed similar procedures to those reported in Study 1; our survey was first written in English, then translated into Russian and Portuguese by native speakers, and then back-translated into English by other Russian and Portuguese native speakers. Participants completed a pencil-and-paper survey that included measures of our constructs of interest (see Study 1 for measurement details and Table 1 for factor loadings, means, and reliabilities). As reported in Table 5, all measures exhibited sufficient convergent and discriminant validity (Fornell & Larcker, 1981). Multi-group CFA analyses also indicated the presence of full metric invariance ($\chi^2$-difference $(17) = 16.58$, $p > .05$) and partial scalar invariance ($\chi^2$-difference $(20) = 60.68$, $p < .05$, CFI and TLI decreased by .01, RMSEA remained the same) (Steenkamp & Baumgartner, 1998).

To determine global and local brand purchases, we asked participants to record if they had purchased/owned products in ten categories: bottled water, soda, laundry detergent, shampoo, chocolates, jeans, shoes, cell-phones, computers, and MP3/CD-players. The categories were selected because they included a range of local and global brands and were relevant to our young adult sample. If participants reported purchasing the products, they then recorded the brand name they had most recently purchased/owned; they could mark “unbranded” if the product did not have a brand name. Two coders (using definitions from Study 1) independently coded a participant’s written brand name responses for each of ten product categories as: “global brand,” “local brand,” or “other” (i.e., brands of unknown origins, foreign brands that are not global, and unbranded products). Coders reached a 98% agreement in Russia and 96% agreement in Brazil; when brand classifications were not in agreement, Euromonitor’s Global Market Information Database and company websites were used to determine the appropriate classification. To derive the percentage of global brands purchased by each cluster, we summed the number of global brands and divided it by the total number of the ten products purchased across the respondents. We followed the same procedure to calculate the percentages of local brands and “other” purchases.

5.2. Results

Again, we first examine the overall sample means on the three global–local identity beliefs (belief in global citizenship through global brands, nationalism and consumer ethnocentrism) that are related to glocal cultural identity. Consistent with Study 1, young adults in Russia and Brazil express significantly stronger nationalistic tendencies ($M_{\text{Russia}} = 4.77$; $M_{\text{Brazil}} = 5.12$) than global citizenship through global brands ($M_{\text{Russia}} = 3.43$; $t(308) = 11.97$, $p < .001$; $M_{\text{Brazil}} = 3.61$ $t(184) = 11.15$, $p < .001$) and consumer ethnocentrism ($M_{\text{Russia}} = 3.38$; $t(308) = 11.97$, $p < .001$; $M_{\text{Brazil}} = 3.02$ $t(184) = 10.14$, $p < .001$).

<table>
<thead>
<tr>
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The idea of a glocal cultural identity is not novel (Cayla & Eckhardt, 2008; Ger & Belk, 1996; Kjeldgaard & Askegaard, 2006); nonetheless, research has yet to offer a systematic investigation into the underlying beliefs that might explain the tensions, complexities, and interplay that occurs in the development of this identity. We suggest that one belief fueled by globalization (global citizenship through global brands) and two beliefs fueled by dialogically-opposed localizational (nationalism and consumer ethnocentrism) can serve as a purchase in the ten product categories, in contrast to 44.8% and 40.2% for the Glocally-engaged and the Nationally-engaged, respectively. We find no differences in the percentage of local brands purchased (−31%) across the segments in Brazil.

Finally, we examined the participants’ use of global and local brands as signals of quality and self-identity in Russia and Brazil. MANOVA results for the use of signals were significant in Russia (Wilks’s $\lambda =$ .73, $F =$ 12.75, $p <$ .001) and in Brazil (Wilks’s $\lambda =$ .70, $F =$ 8.33, $p <$ .001). The four univariate ANOVA tests for global and local signals related to quality and self-identity in each country were significant ($p <$ .001) (see Table 4). In Russia, the pattern of results is consistent with Study 1 findings. Specifically, the Glocally-engaged are more likely to use global and local brands as signals of quality and self-identity than either the Nationally-engaged or the Unengaged; the Nationally-engaged and the Unengaged are similar with regard to consumer use of local brands as symbols of self-identity. In Brazil, the Glocally-engaged and the Glocally-engaged have similar patterns related to global and local brands, with higher use of both global and local brands as signals of quality and self-identity than the Nationally-engaged.

6. Discussion

Global brand managers often assume that the young adult cohort in emerging markets is homogenized and globally-oriented; yet, research indicates that consumers often form glocal cultural identity by blending aspects of their global–local identity beliefs, and, consequently, differentially engage in global and local consumption practices (Ger & Belk, 1996; Hung et al., 2007; Kjeldgaard & Askegaard, 2006; Sceenamp & de Jong, 2010); some researchers have focused on differentiating the global side of consumer identity (Zhang & Khare, 2009), and in our research we use cluster analysis as an alternative technique for assessing glocal cultural identity. Our research integrates and bridges research from two paradigms, consumer culture theory and quantitative globalization studies, and contributes to the stream of glocal identity work in several important ways.

First, we offer a conceptual framework which considers glocal cultural identity as grounded in three global–local identity beliefs (global citizenship through global brands, nationalism, and consumer ethnocentrism). Second, we investigate the understudied young adult cohort in the emerging markets of Russia and Brazil and segment this cohort on their global–local identity beliefs. We then examine the segments’ locally and globally-focused consumption practices as they relate to each segment’s involvement with brands, use of brands as signals of quality and self-identity, and purchase patterns across an array of product categories. Instead of assuming and imposing orthogonality in consumption practices among different segments of local consumers, we show their complexity and highlight both differences and similarities in their responses to marketplace branding realities (consistent with van Ittersum and Wang’s (2010) work on EU consumers). We also incorporate Euromonitor’s Global Market Information Database data on global and local brand market shares for our countries of interest. Third, our findings highlight the evolution of glocal cultural identities within emerging markets.

6.1. Conceptualizing glocal cultural identity and segmenting the young adult cohort

The idea of a glocal cultural identity is not novel (Cayla & Eckhardt, 2008; Ger & Belk, 1996; Kjeldgaard & Askegaard, 2006); nonetheless, research has yet to offer a systematic investigation into the underlying beliefs that might explain the tensions, complexities, and interplay that occurs in the development of this identity. We suggest that one belief fueled by globalization (global citizenship through global brands) and two beliefs fueled by dialogically-opposed localizational (nationalism and consumer ethnocentrism) can serve as a...
basis for examining glocal cultural identity. Segmenting the young adult cohort based on these beliefs resulted in the identification of four segments across our Russian and Brazilian samples and in a pooled sample in Study 2: Globally-engaged, Glocally-engaged, Nationally-engaged, and Unengaged (see Fig. 1). The global–local identity beliefs effectively segment the young adult market. First, a stronger belief in global citizenship through brands differentiates the Globally-engaged and Glocally-engaged from the Nationally-engaged and the Unengaged. Second, a stronger nationalistic tendency differentiates the Globally-engaged, Glocally-engaged, and Nationally-engaged from the Unengaged. Finally, a stronger consumer ethnocentric tendency differentiates the Glocally-engaged from the Glocally-engaged and Nationally-engaged. Furthermore, these beliefs guide consumer consumption practices.

The Glocally-engaged are more likely to use both global and local brands as signals of quality and self-identity and are more involved with both global and local brands than the Nationally-engaged and the Unengaged. The purchases of the Glocally-engaged are reflective of the market structure of global and local brands in Russia and Brazil. The Globally-engaged are similar to the Glocally-engaged in their use of both global and local brands as signals, but report significantly more purchases of global brands (50%) than the Nationally-engaged (40%). The Nationally-engaged are similar to the Unengaged in their lower use of global brand signals and global brand involvement, but the Nationally-engaged report greater use of local brands as signals of quality, stronger involvement with local brands, and more purchases of local brands (18%) than the Unengaged (12%). These findings indicate a more “localized” and less “globalized” response among the Nationally-engaged and speak to the varying nature of young adults’ glocal cultural identity. Finally, the Unengaged appear to have little interest in either patriotic national ideologies or consumption-related discourses, exhibiting nihilistic tendencies across all beliefs.

6.2. The evolution of a glocal cultural identity

Glocal cultural identity takes shape and transforms over time as an individual negotiates between global and local cultures (Arnett, 2002; Eckhardt, 2006; Ger & Belk, 1996; Jensen, 2003, 2011). Our work, by contrasting Russia in 2009 with 2010, and also contrasting Russia with Brazil in 2010, provides an opportunity to speculate about how macro-environmental factors might affect the evolution of glocal cultural identity. Globalization is fueling both economic growth and nationalism in these countries; both countries are receiving increased attention in the global marketplace as a consequence of their BRIC-country status. However, two noticeable differences exist. First, Russia was a closed economy for most of the 20th century and, consequently, its consumers have less experience and exposure to free-market consumption practices than consumers in Brazil. Second, historically rooted nationalism in Russia may evoke stronger nihilistic overtones among Russian consumers than Brazilian consumers.

Given this backdrop, it is perhaps not surprising that Russia’s third segment is the Unengaged, whereas Brazil’s third segment is the Globally-engaged. We speculate that, as Russia becomes a more open multicultural society and Russian consumers gain greater access to and interest in global consumption, we might see a shift in segment size—specifically that the Unengaged segment would become smaller and, over time, that some Glocally-engaged might migrate to a Globally-engaged segment, similar to the segments currently seen in Brazil. In fact, our data show an increase in the size for the Glocally-engaged in Russia from 2009 (41%) to 2010 (50%), which may be partially attributable to several events (measurement error could also account for some variance) that occurred between our 2009 and 2010 data collections: a “reset” of Russia–U.S. relations (“U.S.–Russia relations: “Reset” fact sheet”, 2010, The White House: Office of the Press Secretary), greater partnerships with the BRIC alliance and the hosting its first summit (Buckley & Faulconbridge, 2009), and increased global cooperation because of depressed energy prices. Further, if nationalism escalates in Brazil, the Globally-engaged segment may merge with the Glocally-engaged, and the Unengaged may appear in response to globalization–localization tensions.

Collectively, our findings are consistent with prior research (Jensen, 2003, 2011; Mazzarella, 2003), and demonstrate that consumer glocal cultural identities are not static, but evolving, and that these transformations appear to be more noticeable in markets undergoing greater marketplace shifts (Hermans & Dimaggio, 2007; Kinnvall, 2004).

7. Managerial implications

To be successful in the global marketplace, managers of multinational corporations and local firms need to be cognizant of the glocal cultural identity of young adult consumers. Furthermore, careful consideration of the evolution and dialogical character of glocal cultural identity may be particularly important in emerging markets, where global and nationalistic discourses are intertwined and vying for consumer attention. Our results indicate that young adult consumers can be profiled based on their global–local identity beliefs, and both multinational and local firms launching brands into emerging markets would do well to consider targeting specific glocal cultural identity segments, giving heed to their nationalism, belief in global citizenship through global brands, and consumer ethnocentrism.

Two segments, the Globally-engaged and the Glocally-engaged, are particularly appealing to global firms and brands. These two segments are simultaneously open to global brands and patriotic; they differ, however, in that the latter is more ethnocentric, expressing stronger support of locally-made products. Both segments are engaged in the marketplace, strongly involved with global and local brands, and use both global and local brands to signal quality and self-identity. These segments, particularly the Globally-engaged, are likely to be early adopters of new global brands in their emerging markets. The Glocally-engaged are likely to be the targets of and early adopters of local brands, and could be very effective in helping local firms introduce “cool” local brands to the global marketplace. Ger (1999) suggests that local brands may have deeper and more relevant meanings to consumers than global brands. However, if the Globally-engaged and the Glocally-engaged find resonating meanings in local brands and share them via YouTube, social networks, or Twitter, they may be able to help to elevate them to global brand status. Moreover, these two segments, because of their strong nationalistic tendencies, may become increasingly committed to domestic global brands (Quelch, 2003). More recently, domestic firms in the developing markets of Asia are attempting to re-charge and reshape the image of Asia and its brands as contemporary and hyper-
urban in response to modernity and globalization (Cayla & Eckhardt, 2008). Clearly, the Globally-engaged and Globally-engaged would be responsive targets for marketing campaigns that tap into the global and local aspects of their identity.

The Nationally-engaged segment, defined primarily by their nationalism, should be particularly appealing to local firms. These consumers react more favorably to local than global brands, using them as signals of quality and self-identity. Although this segment purchases a significant percentage of global brands, high-quality local brands would be attractive to them and could ultimately make inroads into the global brand market share. This Nationally-engaged segment presents both challenges and possibilities for multinational firms. In targeting this segment, multinationals would be wise to market brands using local associations, names, and symbolism. Thus, joint-ventures, local production, and culturally-relevant marketing practices—rather than reliance on standardized global marketing practices—would be advised when targeting this segment.

Both local and multinational firms need to acknowledge the Unengaged consumers. These young adults are not engaged in the marketplace and do not use global or local brands as signals of self-identity or quality when making brand choices; they appear to be unresponsive to nationalistic rhetoric. Our results indicate that this segment purchases the same percentage of global brands as other segments, yet these purchases may be convenience-based rather than preference-based. Consequently, if quality local brands become available, their purchase patterns may shift. It may be that these young adults deny that there are unfolding economic and globalization processes, are cynical about them, or rely on alternative consumption cues. Their response to branding appears to be similar to that of “galvanized” consumers (Steenkamp & de Jong, 2010) who are generally uninterested in consumption and may buy whatever is available in the marketplace.

Furthermore, as the marketplace in emerging countries converges and consumption levels become comparable to those in the developed markets (Dholakia & Talukdar, 2004), consumers’ glocal cultural identities are likely to evolve. Thus, both multinational and domestic firms will need to keep the pulse of consumers’ beliefs in global citizenship through global brands, nationalism, and consumer ethnocentrism, and assess how to best manage their portfolio of global and/or local brands. Our work suggests that a glocalized brand approach (Douglas & Craig, 2011; Kapferer, 2001) may be an effective strategy to reach a consumer base that varies on glocal cultural identity.

8. Future research directions

Our research extends the current work on glocal cultural identity with a specific focus on the young adult cohort in emerging markets, and we draw attention to several avenues of research that might be pursued to develop and elucidate additional insights on this domain.

First, we conceptualized glocal cultural identity based on an individual’s global-local identity beliefs of global citizenship through global brands, consumer ethnocentrism, and nationalism. We examined consumer use of global and local brands as signals, global and local brand involvement, and purchases of global and local brands. A broader explication of the glocal cultural identity nomological network is warranted. Specifically, it would be valuable to understand how glocal cultural identity relates to ideological beliefs, such as cosmopolitanism, and consumption traits, such as materialism and innovativeness. Moreover, research is needed to provide a deeper understanding of the socio-historical and political ideological effects on the development and evolution of glocal cultural identity, as well as understanding the personal experiences of consumers reinventing their identities (Coulter et al., 2003).

Second, our work provided insights about glocal cultural identity as related to involvement with brands, the use of brands as signals, and the purchase of global and local brands. Other brand-related variables, such as loyalty, ownership, and the use of brands to signal other meanings, such as traditions or social values, are also of interest. Future research might also investigate the extent to which glocal cultural identity segments use other (non-brand related) consumption cues, such as reliance on peers, family influence, importance of product and ingredient information, and price. Future research could also investigate the potential moderating effects of product category knowledge. Also, to have a better understanding of how glocal cultural identity provides a lens for interpreting marketing stimuli, future work might experimentally examine advertising messages that incorporate different types of globally and/or locally relevant information and symbolism.

Finally, there are several straightforward extensions of our work. For example, researchers might consider glocal cultural identity in other emerging markets. Research has identified similar glocal-local identity belief structures operating in the two other BRIC countries, India and China (Dong & Tian, 2009; Feng, 2004; Kinra, 2006), and based on their economic and political histories and market structure, we speculate that glocal cultural identity segments in India may be more closely aligned with those in Brazil and those in China may span the four segments that we observed across our pooled Russian and Brazilian data. A comparison with consumers in larger or smaller emerging nation-states with weaker protectionist and nationalistic discourses are also of interest and may yield divergent findings. Our focus was on the young adult cohort, but work systematically samples the population at large would provide insights about the existence and size of these glocal segments within a country. Research has suggested that age is a key variable that affects consumer attention to globalization in emerging markets (Coulter et al., 2003; Steenkamp & de Jong, 2010), and so we would expect larger Globally-engaged and Globally-engaged segments among younger populations and larger Nationally-engaged and Unengaged segments among older populations.

9. Conclusion

As emerging nations build their economic power, they are also empowering their national identity in a world filled with global cooperation, global alliances and global media. Nationalistic overtones are frequently mixed with global integration and openness in political and economic dialogues within these emerging markets, impacting the transformation of consumer cultural identity. This domain of research and the examination of these transformations as they relate specifically to glocal cultural identity, as well as variations in meanings of global and national citizenship, will be of growing interest as these emerging countries and their brands take the global stage.

Acknowledgment

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References


Emotions that drive consumers away from brands: Measuring negative emotions toward brands and their behavioral effects

Simona Romani, Silvia Grappi, Daniele Dalli

1. Introduction

Research has largely ignored consumers' negative emotions toward brands, even though consumers increasingly consider the brand-related stimuli when deciding which products and services to consume. The premise that consumers experience strong negative emotions toward brands is interesting given that psychological theories on emotions (Frijda, Kuipers, & ter Schure, 1989; Roseman, Wiest, & Swartz, 1994; Zeelenberg & Pieters, 2006) suggest that the nature of the emotion experienced has a highly determinant effect on an individual's subsequent actions. For example, in general, individuals who experience anger verbally attack the perceived cause of this state, actively seeking a solution. Like anger, fear encourages individuals to take action, but unlike anger, fear motivates them to flee from the fear-evoking stimulus and/or to avoid further confrontation (Roseman et al., 1994). Thus, consumers' anger toward a brand is likely to be predictive of their decision to complain (e.g., file written complaints) to the brand’s parent company and/or to participate in campaigns against the company. On the other hand, fear may predict an unwillingness to try the brand or, if the consumer previously used the brand, the decision to switch to a competing brand. To date, there is no empirically tested measure of negative emotions experienced by consumers when exposed to brand-related stimuli originating from both marketer-controlled and non-marketer-controlled sources of information. Consequently, it is difficult for both researchers and marketing practitioners to understand the nature of these negative emotions and to predict possible negative consumer behaviors toward a brand.

In this paper, which builds on Zeelenberg and Pieters (2006) "Feeling is for Doing" approach and recognizes that the utility of emotions resides in their possible effect on actions, we develop and test a comprehensive scale for measuring specific consumers' negative emotions toward brands. Such a scale is necessary to document consumers' negative reactions to determine their nature, reliability, and construct validity. Moreover, a valid scale is a prerequisite for demonstrating that specific negative emotions are indeed predictive of behavior and, consequently, for a number of empirical and theoretical advancements with respect to emotions and related forms of behavior in a brand-related context.

2. Specific negative emotions and brands

Scholars have examined specific negative emotions generated by products (Laros & Steenkamp, 2005; Nyer, 1997), services (Bougie, Pieters, & Zeelenberg, 2003; Socia, 2007; Zeelenberg & Pieters, 1999, 2004), and purchase-related situations (Dahl, Manchanda, & Argo, 2001; Yi & Baumgartner, 2004). However, few have considered negative emotions toward brands. Although some brand research studies touch upon phenomena closely related to negative emotions and feelings (e.g., Dalli, Romani, & Gistri, 2006; Grant & Walsh, 2009), an explicit consideration of specific negative emotions toward brands and of the emotion–brand behavior link is still lacking in the literature.

In addition to product and service characteristics, consumers are constantly exposed to a variety of brand-related stimuli both from

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A B S T R A C T

Consumers’ appraisals of brand-related stimuli originating from both marketer- and non-marketer-controlled sources of information may evoke negative emotional reactions toward certain brands. We derive a scale that includes six distinct brand-related negative emotions (anger, discontent, dislike, embarrassment, sadness, and worry). Studies 1 through 4 demonstrate that our scale achieves convergent and discriminant validity and provides superior insight and better predictions compared to extant emotion scales. Study 5 manipulates specific negative brand-related emotions and reveals that they predict particular behavioral outcomes (i.e., switching, complaining, and negative word of mouth).

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marketer-controlled sources of information and from other sources. First, consumers come into contact with brand elements (Keller, Apéria, & Georgson, 2008) such as the visual and verbal information that serves to identify and differentiate a brand. Consumers are also exposed to brand-related marketing activities (Brakus, Schmitt, & Zarantonello, 2009). In these activities, marketing communications that function as the voice of the brand, through which it attempts to make contact with consumers, play a fundamental role. Examples of non-marketer-controlled sources of information about brands to which consumers are exposed include information communicated by other commercial or non-partisan sources, word of mouth, and direct personal experiences, as well as anti-brand websites. Finally, consumers autonomously link a brand with people, places, or other elements and consider these additional associations as brand-related stimuli when evaluating the brand (Keller, 2003).

We assume that consumers’ appraisals of brand-related stimuli that are not directly related to product or service attributes and performance constitute the major sources of consumers’ negative emotional responses, referred to here as “negative emotions toward brands” (NEB). We thus conceptualize NEB as consumers’ negative emotional reactions evoked by the appraisal of brand-related stimuli. These stimuli differ from product- or service-related attributes and functions and originate from both marketer-controlled and non-marketer-controlled sources of information.

In addition to irritation or annoyance experienced due to brand slogans (Rosengren & Dahlén, 2006), consumers may also feel distaste toward specific brands because of the undesirable image that the brand’s symbolic meanings project (Hogg & Banister, 2001). Alternatively, the consumers can feel aversion toward a brand based on the identification of that brand with its parent company if the latter is believed to disregard certain basic human rights (Kozinets & Handelman, 2004). Thus, our focus is on negative emotional reactions to brand-related stimuli not directly associated with the actual products or services or with the functions of that product that consumers seek. Although much past brand research has concentrated on tangible, product-related information for brands, branding in recent years has increasingly been about more abstract, intangible, general considerations. These streams of research help to uncover overlooked or relatively neglected facets of consumer-brand knowledge that have significant theoretical and managerial implications (Keller, 2003).

To date, brand research has provided scant information on the negative emotional states that consumers experience in relation to brands. It is not known, for example, if consumers experience predominantly classical emotions such as dislike and anger or if they also experience such emotions as sadness, fear, and shame in relation to brands. Therefore, to identify the full range of negative emotions most frequently experienced in a brand-related context and to construct an appropriate scale for measuring these emotions, it is essential to focus on the common emotion–behavior links in brand-related situations. Consumer behavior scholars have based much of their work related to consumption-related emotions on the Consumption Emotions Set (CES) introduced by Richins (1997). Although this scale has proven useful in the contexts for which it was developed, its usefulness for the study of brand-related negative emotions is limited in several ways that are examined below.

### 3. CES and negative emotions toward brands

The CES plays a central role in the assessment of consumption-related emotions. This scale contains a set of positive and negative descriptors that represent the range of emotions directly experienced by consumers when considering the purchase of a product/service, actually making the purchase, and consuming or using a product/service. Although this measure arguably captures the diversity of emotional states related to consumption experiences better than previous measures in consumer research (Izard, 1977; Plutchik, 1980) or advertising research (Batra & Holbrook, 1990; Edell & Burke, 1987), it is of limited relevance in this study due to the significant differences between negative emotions induced by consumption experiences in general and those arising exclusively in relation to brands.

First, it is unnecessary to consider purchase and actual consumption to assess the emotional states that brands elicit. In fact, some brand-elicited emotions are experienced vicariously rather than directly: consumers may have negative reactions to certain brands of which they are aware but have never personally used. In turn, the nature of the negative emotions experienced toward a brand could partially differ from that of the negative descriptors included in the CES. Thus, the entire range of negative emotions resulting in an unwillingness to try a brand is excluded from the CES.

Second, the negative emotions included in the CES refer to a combination of different situations, actions, and stimuli related to both products and brands. For example, examining the emotions directly experienced during the actual purchase of a specific product requires considering not only the product and possibly the brand (in the case of a brand-focused purchase) but also the interaction with a store’s physical environment, its personnel, and its policies and practices. Under such circumstances, the events and the beliefs about actual or possible causes of these and other product or brand stimuli combine to elicit emotions. The emotional focus of this study is much more specific and limited. We focus on brand-related stimuli that consumers encounter and choose to appraise because of their relevance to the consumer’s well-being (Bagozzi, Gopinath, & Nyer, 1999). In the case of direct experience with a brand, the emphasis is also on the brand, as such, and all of its properties rather than on the various consumption processes involved (such as shopping or usage). For example, together with the depiction of a brand’s target market as communicated through brand advertising, consumers’ own experiences and contacts with brand users can contribute to the formation of a brand-user image that may generate negative emotions toward the brand. However, all that matters for our purposes are the resulting general, unfavorable brand-related associations, not the specific incidents or negative experiences that may contribute to these associations. Given the difference in the referents of emotions, it is reasonable to suggest that the range of negative emotions elicited by brands is more restricted than that elicited by specific consumption experiences. Furthermore, the range of the negative emotions elicited by brands differs partially in terms of the nature of the emotions involved. In fact, the presence of a broader range of emotion elicitors (as in consumption-related rather than brand-related experiences) can make these elicitors interdependent (Ben-Ze’ev, 2000), thus affecting the evaluative patterns and, in turn, the nature of the negative emotions experienced.

In addition, the CES was designed as a comprehensive measurement of the full range of emotional states associated with consumption in numerous contexts; consequently, it is not well suited for the task of addressing specific theoretical issues about negative emotions that are only relevant to brands and potential related emotion–behavior links. It is therefore apparent that the CES has significant shortcomings with respect to assessing negative emotions in relation to brands.

The empirical work presented in this paper is motivated by the desire to identify a more appropriate measure relevant to this issue. This measure’s development is guided by the following objectives: to identify the range of negative emotions most frequently experienced toward brands; to measure these emotions with an acceptable level of reliability; and to test their effects on behavioral outcomes related to brands.

### 4. Consumers’ conceptions of negative emotions toward brands

Before turning to the development of the scale, we present the results of an explorative qualitative study designed to investigate the types of negative emotions that consumers may experience in
relation to brands and the relevant brand-related stimuli that can generate these feelings. For these purposes, Italian consumers (n = 115) were instructed to choose a brand that could generate negative emotional responses and to describe their negative emotions toward it, providing a detailed account of their reasons for these emotions, on a single sheet of paper. The instructions clearly indicated that product or service attributes and performance should not be mentioned as the causes of negative emotions toward the brand. In addition, the survey made no mention of different types of consumption situations or their stages, ranging from anticipatory consumption to usage. This procedure was used in an attempt to focus the respondents’ attention on the brand and, consequently, to reveal the negative emotions related to the abstract, intangible, and general aspects of the brand rather than the negative emotions related to the physical product or service and its consumption per se. Although these dimensions of brand knowledge are related, we believe that they can be distinct and, therefore, are separable. In addition, the participants had to rely on their own perceptions of negative emotions toward brands because they were not primed with specific related terms. Thus, this preliminary study first enabled a conservative assessment of whether consumers react in a way consistent with our conception of negative emotions related to brands. Second, we were able to determine if this type of instruction could focus the respondents’ attention on brand-related stimuli not directly connected to product or service attributes and performance in specific consumption situations.

The majority of the participants provided open-ended responses for a wide variety of goods and service brands. A total of 15% (n = 17) of the respondents were excluded because they described non-emotional responses such as indifference or disinterest. Two expert raters identified the emotion descriptors applicable to negative feelings toward brands that were expressed in each respondent’s written report. The overall inter-rater agreement rate was 91%, with discrepancies resolved through discussion. The respondents used a total of 44 negative emotion descriptors. Those observed most often were angry (n = 15), irked (n = 15), feeling of dislike (n = 15), sad (n = 11), disgusted (n = 9), feeling of hate (n = 9), nervous (n = 8), impatient (n = 7), feeling of distaste (n = 7), and irritated (n = 6). Very few of the most-cited emotion descriptors (i.e., angry, sad, nervous, and irritated) are included in the CES. Impatient is incorporated only in the CES’s extended version, whereas irked is not included as a specific emotion descriptor but, rather, refers to the subcategory of anger in the CES. Furthermore, the remaining most-cited emotion descriptors, such as feeling of dislike, disgust, feeling of hate, and feeling of distaste, are absent from the CES. In our opinion, and according to Ortony, Clore, and Collins’s (1988) taxonomy, these absent descriptors refer to an emotion subcategory that was excluded from CES: dislike. Conversely, some emotion descriptors and emotion subcategories included in the CES (e.g., envy and guilt) do not appear in our data. Therefore, this preliminary qualitative study suggests that the CES is a brand that I consider as not representing me at all! A brand for showgirl types! Think about its ads and endorsers (f, 21).

Brand-related stimuli from non marketer-controlled sources of information

- I hate this brand. I also read a newspaper article recently about its brand personality and values, and I really don’t understand how they can continue using these old-fashioned ideas and narratives (f, 41).

- Feel disgust toward this brand! Have you ever tried passing in front of one of its outlets? The smell is terrible! I could never go in! (m, 35).

- Brand-related stimuli from consumers’ associations of brands with other relevant entities (companies, countries, spokespersons, etc.)

- I hate the exploitation and total lack of ethics that are behind every one of this brand’s products (f, 20)

- I really hate this brand because of its business practices... I also participate in web groups against it! It’s a useful way to express my negative feelings... (m, 35)

that, in line with our definition of NEB, the participants described all of the possible types of brand-related stimuli as sources of their negative emotions. Moreover, the respondents did not refer to specific incidents or experiences with a brand in their narratives; rather, they relied on more general and abstract brand-related information.

A final point worth noting is that almost all of the descriptions of the causes of negative emotions were related to brand stimuli different from typical negative product or service attributes and performance. This evidence supports the appropriateness of the selected procedures for the scope of this research.

In summary, this preliminary qualitative study provides us with the opportunity to better understand negative emotions toward brands and supports the need to identify a more appropriate instrument for measuring these emotions. We now turn our attention to the development of a reliable measurement instrument to empirically demonstrate specific associations between negative emotions and behaviors in a brand-related context.

5. Developing the NEB scale

Studies 1 and 2 develop the NEB scale; study 3 validates its internal consistency, defines its dimensional structure, and assesses its convergent and discriminant validity. Lastly, study 4 concludes the demonstration of the NEB’s superiority in terms of predictive validity compared to the CES.

5.1. Study 1

This initial study aimed to identify a preliminary set of descriptors for the range of negative emotions that consumers experience toward brands. We asked 106 Italian undergraduate and graduate students (45% female, 55% male; all between 20 and 27 years of age) from a cross-section of majors to identify a brand capable of generating negative emotional responses, following the procedure illustrated above in the preliminary study. In addition to the benefits for the scope of our research, this data collection methodology is characterized by brand heterogeneity across respondents, with references made to various brands that engender different types and degrees of negative emotions. Therefore, this methodology led to the selection of a set of items and then to the identification of a set of factors that cover the full range of possible negative feelings that consumers experience toward brands.

Table 1

<table>
<thead>
<tr>
<th>Brand-related stimuli capable of generating negative emotions.</th>
</tr>
</thead>
<tbody>
<tr>
<td>The brand-name is ridiculous, as are the logo and slogan; I don’t like anything about this brand (f, 23).</td>
</tr>
<tr>
<td>This is a brand that I consider as not representing me at all! A brand for showgirl types! Think about its ads and endorsers (f, 21).</td>
</tr>
<tr>
<td>Brand-related stimuli from non marketer-controlled sources of information</td>
</tr>
<tr>
<td>I hate this brand. I also read a newspaper article recently about its brand personality and values, and I really don’t understand how they can continue using these old-fashioned ideas and narratives (f, 41).</td>
</tr>
<tr>
<td>Feel disgust toward this brand! Have you ever tried passing in front of one of its outlets? The smell is terrible! I could never go in! (m, 35).</td>
</tr>
<tr>
<td>Brand-related stimuli from consumers’ associations of brands with other relevant entities (companies, countries, spokespersons, etc.)</td>
</tr>
<tr>
<td>I hate the exploitation and total lack of ethics that are behind every one of this brand’s products (f, 20).</td>
</tr>
<tr>
<td>I really hate this brand because of its business practices... I also participate in web groups against it! It’s a useful way to express my negative feelings... (m, 35).</td>
</tr>
</tbody>
</table>

1 Some of the selected brands were recently involved in a product-harm crisis (e.g., Nestlé in China). Although these events may “devastate a carefully nurtured brand equity” (Van Heerde, Helsen, & Dekimpe, 2007, p. 230), our respondents did not refer to these events, focusing more on general issues related to their brand knowledge.

2 This procedure was used in all four studies. Study 5 was characterized by some differences in the procedure used, as illustrated in Section 6.1.

3 It is important to note that similar results are unlikely to be obtained using alternative methods, such as asking respondents to report their negative responses to an individual, typically “controversial” brand, because this is likely to restrict the scope to certain negative emotions evoked by the selected brand.
The participants completed a survey comprising 106 negative emotion descriptors. The emotion descriptors spanned the range of negative emotions identified by the respondents in the qualitative exploratory study as well as those identified by other scholars (e.g., Lars & Steenkamp, 2005; Ortony et al., 1988). Given that the literature on this topic is essentially U.S.-based, the negative emotion descriptors were collected in English. These items were then translated into Italian using a double-back-translation method with independent translators (Brilin, 1980). The respondents used 7-point rating scales ranging from 1 (not at all) to 7 (very much) to describe the extent to which the selected brand made them feel each of the 106 emotion descriptors. Two versions of the questionnaire were prepared, one with the emotion descriptors in alphabetical order and the other in reverse, to control for possible order effects.

For this study, 73 brands were considered capable of generating negative emotion responses. The respondents mainly selected brands related to clothes and fashion accessories (37%), groceries (22%), cars (13%), and audio/video equipment (9%). Any emotion descriptor with a mean value above 2 on the 7-point scale was assumed to have significance. The remaining 87 negative emotion descriptors were subjected to maximum likelihood exploratory factor analysis with oblique rotation (promax). Any item with a factor loading greater than .50 on its focal factor and not higher than .25 on another was retained. Six different factors (χ²(165) = 202.4; p = .02) were identified, containing 25 negative emotion descriptors in total, which were then used in the subsequent study. The Cronbach’s alphas of the six dimensions are sufficiently high, ranging from .69 to .86. The six factors account for 68.4% of the total variance, and the factors are clearly different. The factor labeled ‘dislike’ included items for feeling contempt, revulsion, and hate. These emotion descriptors imply consumers’ rejection of the brand based on evaluations of unappealingness. The factor labeled ‘sadness’ included items for heartbroken, sorrowful, and distressed. These reflect the unpleasant emotions consumers may experience toward a brand due to an undesirable outcome. The factor labeled ‘discontent’ included items for feeling dissatisfied, unfulfilled, and discontented, which describe consumers’ negative feelings when their expectations are disconfirmed or not met. The factor labeled ‘anger’ included items for indignant, annoyed, and resentful, reflecting the varying levels of intensity of the anger consumers feel toward a brand, usually due to a fairly specific cause such as provocation or a violation of principles. The factor labeled ‘worry’ included items covering feeling threatened, insecure, and worried. These suggest that consumers consider a brand as potentially dangerous and/or threatening to themselves. Finally, the factor labeled ‘embarrassment’ included items for feeling sheepish, embarrassed, and ridiculous, thus reflecting consumers’ negative feelings regarding both the personal and social disadvantages of being associated with a brand.

### Table 3

Study 2 — correlations between dimensions (std errors).

<table>
<thead>
<tr>
<th></th>
<th>Dislike</th>
<th>Sadness</th>
<th>Discontent</th>
<th>Worry</th>
<th>Anger</th>
<th>Embarrassment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dislike</td>
<td>.10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sadness</td>
<td>.04</td>
<td>.07</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discontent</td>
<td>.07</td>
<td>.08</td>
<td>.07</td>
<td>.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Worry</td>
<td>.10</td>
<td>.08</td>
<td>.04</td>
<td>.04</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anger</td>
<td>.07</td>
<td>.05</td>
<td>.02</td>
<td>.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Embarrassment</td>
<td>.04</td>
<td>.06</td>
<td>.00</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

|                | .01     | .00     | .01        | .00   |       |               |

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

In this study, 146 different brands were considered capable of generating negative emotion responses. The respondents mainly selected brands related to clothes and fashion accessories (36%), groceries (25%), hi-fi/audio/video equipment (10%), and cars (8%). The negative emotion descriptors were subjected to maximum likelihood exploratory factor analysis with promax rotation. Any item with a factor loading greater than .50 on its focal factor and no loading higher than .25 on another factor was retained. Furthermore, items with mean ratings below 2 were eliminated. The final set reflected six factors (χ²(60) = 84.2, p = .02) containing 18 negative emotion descriptors (see Table 2).

The factor labeled ‘dislike’ included items for feeling contempt, revulsion, and hate. These emotion descriptors imply consumers’ rejection of the brand based on evaluations of unappealingness. The factor labeled ‘sadness’ included items for heartbroken, sorrowful, and distressed. These reflect the unpleasant emotions consumers may experience toward a brand due to an undesirable outcome. The factor labeled ‘discontent’ included items for feeling dissatisfied, unfulfilled, and discontented, which describe consumers’ negative feelings when their expectations are disconfirmed or not met. The factor labeled ‘anger’ included items for indignant, annoyed, and resentful, reflecting the varying levels of intensity of the anger consumers feel toward a brand, usually due to a fairly specific cause such as provocation or a violation of principles. The factor labeled ‘worry’ included items covering feeling threatened, insecure, and worried. These suggest that consumers consider a brand as potentially dangerous and/or threatening to themselves. Finally, the factor labeled ‘embarrassment’ included items for feeling sheepish, embarrassed, and ridiculous, thus reflecting consumers’ negative feelings regarding both the personal and social disadvantages of being associated with a brand.

A confirmatory factor analysis (CFA) confirmed the validity of our six factors (χ²(120) = 174.49; NNFI = .93; CFI = .95).

** This factor’s label was inspired by the concept of dislike presented by Ortony et al. (1988). These emotions are momentary reactions of dislike that distinguish from dispositional dislike, usually called negative attitudes. The latter can influence the former. People are more likely to experience momentary emotions of dislike toward particular objects if they have a dispositional dislike for the general categories to which the objects can be assigned. The central idea is that this group of emotions includes reactions of momentary dislike, but the unappealingness variable that drives them is based on dispositional dislike, and the two, despite interacting in important ways, clearly differ.
RMSEA = .04; SRMR = .05) (1JSREL, Jöreskog & Sörbom, 1996). The correlations between the dimensions obtained through the CFA are presented in Table 3. This descriptor set, referred to as NEB, is expected to adequately represent consumers’ negative emotional reactions to brands. Some specific emotions that are usually important in consumption contexts, such as guilt or envy, are not present in our scale. This absence can be explained in several ways. First, to keep the scale as short as possible, we excluded from the analyses the negative emotions that were less prominent in respondents’ answers, including guilt and envy. However, the low prominence of these two negative emotions in our research context can be derived, as explained in Section 3, from the specific referent of emotions considered in the NEB scale. Our focus on brand-related stimuli rather than on consumption-related situations can justify the absence of both guilt and envy from the NEB scale.5

5.3. Study 3

5.3.1. Objectives and method

Study 3 was designed to confirm the NEB scale’s stability using a different sample of respondents (ordinary consumers) and to assess the possible hierarchical relation among the first-order factors representing the construct of negative emotions toward brands; that is, the possibility of second-order factors was investigated. A multitrait-multimethod (MTMM) matrix analysis was performed to confirm the validity of our measures (Bagozzi & Edwards, 1998; Bagozzi & Yi, 1991, 1993; Bagozzi, Yi, & Philips, 1991), taking alternative measures from previous research on emotions in marketing and consumer behavior into consideration as different methods. We specifically included measures from the CES, and for the sake of comprehensiveness, we included measures from two other emotion scales frequently used in consumer research: Izard’s (1977) DES-II scale and Havlena and Holbrook’s (1986) adaptation of Plutchik’s scale.

A total of 421 ordinary Italian consumers (40.6% male, 50.4% female; aged between 18 and 86 years, with a mean age of 42 years) were asked to recall a brand toward which they felt negative emotions and to complete the 18-item NEB scale with this brand in mind. In addition, to carry out the MTMM analysis, the questionnaire included negative emotion descriptors from the previously mentioned scales that were not included in the NEB scale. The respondents used a 7-point rating scale ranging from 1 (not at all) to 7 (very much) to quantify the extent to which the selected brand evoked the appropriate negative emotions.

In this study, 243 different brands were nominated as capable of generating negative emotional responses. The respondents mainly selected brands related to groceries (30%), clothes and fashion accessories (27%), cars (15%), and hi-fi/audio/video equipment (8%). There were no important differences in terms of brand and product categories between the student and the ordinary consumer samples. This reduces the risk of effects on responses due to different brand and product categories that respondents referred to in the generation phase or validation process.

5.3.2. Results

Structural equation modeling was used to assess the scale items’ relationships with the construct of negative emotions toward brands. Cronbach’s alpha reliability coefficients for the measures were all satisfactory (α = .70). A CFA confirmed that the six factors were valid

5 Feelings of guilt have been linked to compulsive buying (O’Guinn & Faber, 1989), to specific interactions with salespeople (Dahl, Honea, & Manchanda, 2005), and to the consumption of unethical products (Bray, John, & Kilburn, 2011). In all of these situations, consumers experience guilt when they appraise their bad consumption actions. A similar argument can be used with respect to envy. This is an emotion that can become prominent when actual consumption, imagined consumption, or even observed consumption by others is involved, as illustrated by Van de Ven, Zeelenberg, and Pieters (2010).

Table 4 presents the correlations between the dimensions (i.e., factors).6

Conversely, Table 3 shows the correlations between the dimensions (std. errors).

Table 3 – correlations between dimensions (std. errors).

<table>
<thead>
<tr>
<th>Dislike</th>
<th>Sadness</th>
<th>Discontent</th>
<th>Worry</th>
<th>Anger</th>
<th>Embarrassment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dislike</td>
<td>1.00</td>
<td>.34** (.06)</td>
<td>.04 (.06)</td>
<td>.39** (.06)</td>
<td>.75** (.06)</td>
</tr>
<tr>
<td>Sadness</td>
<td></td>
<td>1.00</td>
<td>.02 (.06)</td>
<td>.01 (.06)</td>
<td>.46 (.06)</td>
</tr>
<tr>
<td>Discontent</td>
<td></td>
<td></td>
<td>.04 (.06)</td>
<td>.25 (.06)</td>
<td>1.00</td>
</tr>
<tr>
<td>Worry</td>
<td></td>
<td></td>
<td></td>
<td>.25 (.06)</td>
<td>1.00</td>
</tr>
<tr>
<td>Anger</td>
<td></td>
<td></td>
<td></td>
<td>.49 (.06)</td>
<td>1.00</td>
</tr>
<tr>
<td>Embarrassment</td>
<td></td>
<td></td>
<td></td>
<td>.49 (.06)</td>
<td>1.00</td>
</tr>
</tbody>
</table>

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

6 We also performed the likelihood ratio test (Anderson & Gerbing, 1988; Bollen, 1989) to confirm the NEB constructs’ discriminant validity compared to the attitude toward the brand. The following items were used to measure attitude: bad–good, unpleasant–pleasant, low quality–high quality, worthless–valuable, useful–useless, unfavorable–favorable, disadvantageous–advantageous, negative–positive, unpleasant–pleasant, agreeable–disagreeable (α = .88). The likelihood ratio test, performed separately for each NEB factor and attitude, provides evidence for discriminant validity. The chi-squared statistic that explicitly compares models suggests that the model without constriction is significantly better than models that hypothesize equality between the attitude toward the brand and the NEB factors (attitude = anger, $\chi^2$ = 88.84; df = 1. α = .05; attitude = dislike, $\chi^2$ = 103.57; df = 1. α = .05; attitude = worry, $\chi^2$ = 45.19; df = 1. α = .05; attitude = sadness, $\chi^2$ = 6.14; df = 1. α = .05; attitude = embarrassment, $\chi^2$ = 51.13; df = 1. α = .05; attitude = discontent, $\chi^2$ = 4.4; df = 1. α = .05).
The discontent dimension requires specific comments. Unlike the other specific negative emotions, relatively little is known about the nature and experience of discontent. In general, research in psychology (e.g., Ortony et al., 1988; Scherer, 1994) and marketing (e.g., Bougie et al., 2003; Nyer, 1998) converges on considering the emotion descriptors in this category as relatively undifferentiated emotions; that is, general valenced reactions to negative events. In addition, Weiner (1986) depicts this emotion group as outcome-dependent emotions because they are associated with the undesirability of an event, not with its cause. Specific evidence for this conceptualization in a marketing context is provided by Bougie et al. (2003), who show that feelings of dissatisfaction resulting from service failures are distinct from more specific negative emotions (anger, in this specific study) that may arise following attempts to determine why the service failure occurred. This conceptualization suggests that we should treat discontent in the model as a specific negative emotion separate from the other cause-related negative emotions (Roseman et al., 1996). Moreover, the special nature of discontent may also suggest a possible explanation for the low correlations with the more differentiated negative emotions.7 Therefore, in terms of model design, it is possible to assume six first-order latent factors (anger, dislike, embarrassment, worry, sadness, and discontent), four of which reflect second-order factors (NEB1 and NEB2) (model 3) (see Fig. 1). This model’s goodness-of-fit is satisfactory: \( \chi^2(136) = 309.84; \) NNFI = .90; CFI = .91; RMSEA = .05; SRMR = .06.

In model 3, anger and dislike, as well as sadness and worry, are first-order factors that correspond to two higher-order constructs, whereas embarrassment and discontent are distinct negative emotions at the first-order level. Likelihood ratio tests show that the four constructs in model 3 (discontent, embarrassment, NEB1, and NEB2) are distinct dimensions.8

An analysis of a MTMM matrix was then carried out to confirm construct validity using the following alternative measurement scales: the NEB scale and measures from Richins (1997) CES scale, Havlena and Holbrook’s (1986) adaptation of Plutchik’s scale, and Izard’s (1977) DES-II scale as two methods (see below). Consequently, we were able to assess construct validity, estimating and adjusting for random error and method variance influences. Given the lack of alternative measures available to form an indicator for the second method of the discontent dimension, we eliminated it from this analysis. The discontent dimension, in fact, is only present in the CES scale with two items that correspond to two of the three items included in our NEB scale; therefore, it is not possible to include this dimension in the current analysis. The CFA for the MTMM consists of five traits (anger, dislike, embarrassment, worry, and sadness) and two methods (the NEB scale as method 1 and measures selected from Richins (1997) CES scale, Havlena and Holbrook’s (1986) adaptation of Plutchik’s scale, and Izard’s (1977) DES-II scale as method 2). All participants in the sample responded to all of the items in both methods. The selected measures comprising the factors in method 2 are irritated, angry, hostile, and enraged for anger; disgusted and disdainful for dislike; ashamed, humiliated, and shy for embarrassment; scared, afraid, and fearful for worry; as well as sad, miserable, and downhearted for sadness.

As previously mentioned, all three measurement scales were used for greater completeness and because the CES scale is incapable of covering all of the traits included in the NEB scale. In addition, specific measures were selected from each of the three competing scales based on an evaluation of the items that could best map our traits. The CFA model of MTMM fits the data very well: \( \chi^2(14) = 19.82, p = .14; \) NNFI = .99; CFI = 1.00; RMSEA = .03; SRMR = .02. To confirm that both trait and method factors are necessary to explain the variance in the measures, we compared this model with the trait-only model. The comparison of the two models indicated that the introduction of method factors shows significant improvements over the trait-only model (\( \Delta \chi^2(\Delta df = 11) = 58.6, p < .01 \)). Therefore, we used the trait-method-error model to test construct validity. Trait variance was used to indicate the degree of convergent validity (Widaman, 1985), and all factor loadings for traits proved to be statistically significant, ranging from moderate to high in magnitude. The random error variances ranged from very low to moderate in magnitude, as did the method variance. Overall, the convergent validity of the NEB scale measures was demonstrated. Furthermore, all traits achieved discriminant validity because the correlation plus 2 standard errors between each pair was less than 1.00 at the .05 level of significance.

5.3.3. Discussion

Study 3 presents an NEB scale structure based on two higher-order constructs (anger–dislike and sadness–worry) and embarrassment and discontent as single, specific emotions. We acknowledge that the two composite, higher-order constructs resulting from second-order factor analysis may be unique to how responses were generated in the present study and that, in any given context, consumers may or may not exhibit second-order representations of their negative emotions toward brands. In other words, it is possible that, in certain situations, people experience strong worry but weak sadness or strong anger but weak dislike and so on. Nevertheless, it is possible to use our items to measure all of these reactions because the NEB scale can be employed to represent emotional responses as first-order factors if desired. In addition, the higher-order constructs, although empirically and theoretically relevant, are nevertheless formed by individual emotions that, despite sharing a degree of similarity in terms of appraisal (Roseman et al., 1996), differ substantially with regard to experiential content (Roseman et al., 1994). Accordingly, these individual emotions were treated separately in the final part of this research, which utilizes specific negative emotions toward brands to predict specific forms of consumer behavior.

Furthermore, study 3 supports the construct validity of the NEB measures when compared to the other relevant scales in the literature. Thus, the need to create a specific set of emotion descriptors that can be used to assess negative emotions toward brands has been met.

5.4. Study 4

5.4.1. Objectives and method

This study was designed to examine the predictive validity of the NEB in comparison to the CES. Because the NEB scale was specifically developed to measure negative emotions toward brands, it should be superior to the CES—a consumption emotion scale—in explaining relevant forms of consumer behavior related to brands. Specifically, we compare the ability of the NEB and the CES scales to effectively predict three forms of subsequent behavior, namely, complaining, switching, and word-of-mouth communication. Vandecasteele and Geuens (2010) used a similar procedure to demonstrate the predictive validity of their motivated consumer innovativeness scale.

We collected data from a sample of 146 ordinary Italian consumers (50% male, 50% female; aged between 18 and 69 years, with a mean age of 30 years). They were asked to recall a brand toward which they felt negative emotions and to complete the items on the NEB scale and the negative items on the CES scale with this brand in mind. The respondents used 7-point rating scales ranging from 1 (not at all) to 7 (very much) to describe the extent to which the selected brand made them feel each of the different emotion descriptors presented in the questionnaire. The items that belong to both the NEB and CES scales were measured only once; in total, the

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7 Although the discontent factor presents low correlations with the other factors, we decided to retain it in the following analyses because it contributes to the content of the scale, as suggested by Rossiter (2002) and Vandecasteele and Geuens (2010).

8 Chi-squared difference tests of each correlation show that NEB1 and NEB2 are distinct (\( \Delta \chi^2(1) = 133.37, p < .05 \)), as are NEB1 and embarrassment (\( \Delta \chi^2(1) = 516.99, p < .05 \)), NEB2 and embarrassment (\( \Delta \chi^2(1) = 144.41, p < .05 \)), discontent and embarrassment (\( \Delta \chi^2(1) = 391.32, p < .05 \)), NEB1 and discontent (\( \Delta \chi^2(1) = 495.74, p < .05 \)), and NEB2 and discontent (\( \Delta \chi^2(1) = 273.56, p < .05 \)).
subjects answered to 37 negative emotion descriptors. In addition, the questionnaire included the following measures.

5.4.2. Brand switching
Brand switching was measured with a 3-item adapted subset of Bougie et al.’s (2003) scale ($\alpha = .76$). The respondents completed a 7-point agreement scale ranging from 1 (not at all) to 7 (very much) for the items “I bought this brand less frequently than before,” “I switched to a competing brand,” and “I stopped buying this brand, and I will not buy it anymore in the future.”

5.4.3. Negative word of mouth
Negative word of mouth was measured using an adaptation of Bougie et al.’s (2003) scale ($\alpha = .95$). The respondents completed a 7-point agreement scale to address the following questions: “I said negative things about this brand to other people,” “I discouraged friends and relatives to buy this brand,” and “I recommended not to buy this brand to someone who seeks my advice.”

5.4.4. Complaining
Complaining was measured using a subset of Zeelenberg and Pieters (2004) scale ($\alpha = .89$). A 7-point agreement scale was used to address the following questions: “I complained to external agencies (e.g., consumer unions) about the brand,” “I complained to the company that produces the brand,” and “I filled written complaints to the company that produces the brand.”

5.4.5. Results
In separate analyses of each scale, the variables of the three forms of behavior were used to form the dependent variable set, while the subscales of the NEB measure and, separately, the subscale of the CES formed the predictor variable set. The resulting $R^2$ and chi-squared values of these sets of regression analyses are shown in Table 5.

Although the NEB scale is formed by six factors and the CES scale by nine, the results show that the NEB scale is superior in representing the variance of the relevant outcomes of switching and negative word of mouth. With respect to these two types of behavior and compared to the CES, the NEB can account for a greater part of the variance. With respect to complaining behavior, the NEB and CES scales appear not to differ in capturing the variance of the outcome. The CES scale less adequately predicts switching and negative word of mouth, accounting for less than 20% of the variance, whereas the

### Table 5

<table>
<thead>
<tr>
<th></th>
<th>CES</th>
<th>NEB</th>
<th>Likelihood ratio test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$; chi-squared (df)</td>
<td>$R^2$; chi-squared (df)</td>
<td>$\Delta$chi-squared (df); $p$</td>
</tr>
<tr>
<td>Complaining</td>
<td>.24; 51.11 (9)</td>
<td>.25; 48.37 (6)</td>
<td>.75 (3); $\alpha &lt; .05$</td>
</tr>
<tr>
<td>Negative WOM</td>
<td>.14; 64.29 (9)</td>
<td>.33; 30.26 (6)</td>
<td>34.03 (3); $\alpha &lt; .05$</td>
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<tr>
<td>Switching</td>
<td>.18; 39.26 (9)</td>
<td>.28; 29.06 (6)</td>
<td>10.02 (3); $\alpha &lt; .05$</td>
</tr>
</tbody>
</table>

Fig. 1. Confirmatory factor analysis, (the model hypothesizes six first-order factors explained by two second-order factors, labeled NEB1 and NEB2; measurement error terms omitted for simplicity).
NEB scale explains 28% and 33%, respectively, of the variances of each of these behavioral responses.

5.4.6. Discussion

Study 4 confirms the superiority of the NEB scale over the CES when their predictive ability is considered regarding relevant negative forms of consumer behavior related to brands. Therefore, we conclude that the NEB scale shows incremental validity (Netemeyer et al., 2003) over the CES. Having demonstrated that the new scale provides superior insights and better predictions than extant scales, especially the CES, in the next study, we focus our attention on the NEB scale to test important theoretical issues regarding specific negative emotions relevant to brands and the relative emotion-behavior links in brand-related contexts.

6. Study 5: using specific negative emotions included in the NEB scale to predict consumer behavior

In study 5, we focus on the three key behavioral outcomes: switching, negative word of mouth, and complaining. On the basis of prior studies in psychology and consumer research, we expect that the specific negative emotions included in the NEB scale affect consumers’ behavioral outcomes in different ways.

First of all, we note that not all emotions are clearly associated with well-defined actions. This is best exemplified by sadness, which is typically defined in terms of inactivity or the absence of any well-defined type of activity (Izard & Ackerman, 2000; Mattsson, Lemmink, & McColl, 2004; Shaver, Schwartz, Kirson, & O'Connor, 1987). Hence, we expect that sadness is not likely to have a significant effect on consumers’ negative behavioral responses to brands.

A similar argument can be used for discontent. This is a consumer’s general valenced reaction to a negative event that normally motivates him or her to find out the reason why the event occurred and to examine who or what is responsible but not to immediately act (Bougie et al., 2003). Therefore, we expect that discontent will have no significant effect on consumers’ negative behavioral responses to brands.

As for the other emotional responses to brands, we maintain that the “feeling is for doing” perspective is applicable and, accordingly, assign actions to emotions based primarily on previous psychological research (e.g., Bougie et al., 2003; Frijda et al., 1989; Oatley & Jenkins, 1996; Roseman et al., 1994; Shaver et al., 1987). Specifically, we predict that worry will have a significant (positive) influence on switching because this emotion is commonly found to be a response to perceived threats to oneself (Oatley & Jenkins, 1996), rousing individuals to action and especially motivating people to flee from a situation in an effort to avoid dangerous outcomes. In brand-related contexts, worry should therefore lead to brand switching.

We also predict that anger will have a significant (positive) influence on complaining, given that this emotion generally elicits the opposite reaction of worry. Although both worry and anger clearly activate individuals, only the latter motivates them to actively seek a solution to the situation (Roseman et al., 1994; Shaver et al., 1987; Stephens & Gwinner, 1998) by attacking or lashing out at the source of the anger. Consequently, in brand-related contexts, anger is expected to lead to complaining.

Likewise, we can predict that dislike will have a significant (positive) influence on both negative word of mouth and switching because individuals wish to distance themselves from, reject, express their disapproval of, or be disassociated from someone or something they dislike (Roseman et al., 1994). Thus, in brand-related contexts, dislike is likely to lead to both negative word of mouth as a way of expressing disapproval of or disassociation from the brand and to switching as a means of rejecting a previously used brand.

Finally, we expect embarrassment to have a significant (negative) influence on complaining because, in the presence of this emotion, individuals tend to turn inward and avoid contact with others (Roseman et al., 1994). We conclude, therefore, that embarrassment is likely to inhibit complaining.

6.1. Method

We collected data from a sample of ordinary Italian consumers to address issues of generalizability and external validity. We conducted a study using 1217 individuals (47% male, 53% female, aged between 18 and 89, with a mean age of 41). We developed a “recalled emotion” condition for each of the six negative emotions that the NEB scale measures. For each of these, the respondents were asked to identify a brand that evoked the assigned negative emotion in them. For example, if the recalled emotion condition was dislike, the respondents were asked to take a few minutes to identify a brand they disliked. They were then asked to recall reasons for the negative emotion related to this brand as vividly as possible before providing written, open-ended responses to questions about the brand. This procedure encouraged recollection of brand knowledge prior to completing the questionnaire.9 For a similar procedure, see Roseman, Spindel, and Jose (1990). The respondents then completed the items of the NEB scale with this brand in mind. In addition, to demonstrate that specific negative emotions have different consequences for consumers’ negative behavioral responses toward brands, the questionnaire included the same measures used in study 4 for switching ($\alpha = .81$), negative word of mouth ($\alpha = .93$), and complaining ($\alpha = .75$).

6.2. Results

Table 6 shows the mean values of the emotions experienced by the six recalled emotion conditions. The diagonal entry is the highest number in each of the table’s rows and columns. This means that a given experienced emotion was highest in its corresponding recalled emotion condition (e.g., dislike was experienced to a higher degree in the recalled emotion condition dislike than in the other recalled emotion conditions). An ANOVA analysis was conducted to compare each of the experienced emotions among the six recalled emotion conditions: dislike, $F(5, 1210) = 222.29, p < .001$; anger, $F(5, 1211) = 157.55, p < .001$; sadness, $F(5, 1209) = 137.43, p < .001$; worry, $F(5, 1210) = 351.44, p < .001$; embarrassment, $F(5, 1210) = 448.56, p < .001$; and discontent, $F(5, 1210) = 192.17, p < .001$. In addition, for a given recalled emotion condition, the targeted emotion was always the significantly dominant experienced emotion (Table 7). For example, in the case of the dislike recalled emotion condition, we compared the mean of dislike with the means of the other negative emotions experienced within the same condition using the t-test statistic (e.g., $M$(dislike) = 6.16 vs. $M$(anger) = 4.38; $t = -16.55, p < .001$). Overall, these findings demonstrate that the recall instructions were, to a significant degree, successful in stimulating the retrieval of brands that could elicit the targeted emotions. Table 8 displays the mean values of the three behavioral measures used to assess the predictive validity of the recalled emotion conditions. The F-values assessed the statistical significance of differences in consumers’ negative behavioral responses toward the brand across all of the recalled emotion conditions.

Having demonstrated that the recall instructions have a significant effect on emotions and behaviors, the next step was to verify whether the effects on behaviors are really due to the mediating

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9 Two expert raters coded the descriptions of the reasons that the respondents gave for the negative emotions that they reported. Almost all of them provided causes of negative emotions related to brand stimuli other than product or service failures. They usually relied on general and abstract brand-related information, providing abstractions of specific consumption situations. This additional evidence confirms the selected procedure’s validity for our research scope.
Table 6
Study 5 — means and ANOVAs of the experienced emotions among the different recalled emotion conditions.

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<td>Mean (SD)</td>
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<td>3.62 (1.5)</td>
<td>2.20 (1.5)</td>
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<td></td>
<td>2.84 (1.5)</td>
<td>2.98 (1.6)</td>
<td>2.24 (1.6)</td>
<td>2.24 (1.6)</td>
<td>2.98 (1.6)</td>
<td>3.68 (1.6)</td>
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<tr>
<td>Anger</td>
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<td>2.43 (1.6)</td>
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<td>F(5, 1211) = 157.55, .40</td>
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<td>1.54 (1.6)</td>
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<td>1.54 (1.6)</td>
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<tr>
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<td>5.00 (1.5)</td>
<td>2.20 (1.5)</td>
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<td>1.84 (1.5)</td>
<td>F(5, 1208) = 137.43, .36</td>
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<td></td>
<td>2.22 (1.5)</td>
<td>1.51 (1.5)</td>
<td>1.23 (1.5)</td>
<td>1.23 (1.5)</td>
<td>1.22 (1.5)</td>
<td>1.22 (1.5)</td>
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<tr>
<td>Worry</td>
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<td>2.01 (1.4)</td>
<td>5.92 (1.4)</td>
<td>2.15 (1.4)</td>
<td>1.95 (1.4)</td>
<td>1.84 (1.4)</td>
<td>F(5, 1212) = 351.44, .59</td>
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<td></td>
<td>1.23 (1.4)</td>
<td>1.25 (1.4)</td>
<td>1.23 (1.4)</td>
<td>1.23 (1.4)</td>
<td>1.19 (1.4)</td>
<td>1.20 (1.4)</td>
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<tr>
<td>Embarrassment</td>
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<td>1.65 (1.3)</td>
<td>1.69 (1.3)</td>
<td>5.84 (1.3)</td>
<td>1.69 (1.3)</td>
<td>6.33 (1.3)</td>
<td>F(5,1210) = 448.56, .65</td>
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<tr>
<td>Discontent</td>
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<td>4.02 (1.4)</td>
<td>3.12 (1.4)</td>
<td>2.67 (1.4)</td>
<td>6.33 (1.4)</td>
<td>4.02 (1.4)</td>
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<tr>
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<td>1.43 (1.4)</td>
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</table>

ANOVA were performed on each experienced emotion among the different recalled emotion conditions. The means with different subscripts differ significantly (Tukey post-hoc test). The higher experienced emotion is indicated with (a). Bold values are the highest experienced emotion condition coefficients in the corresponding recalled emotion condition.

Table 7
Study 5 — means and t-test statistics of the experienced emotions by recalled emotion conditions.

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<td>Mean (SD)</td>
<td>Mean (SD)</td>
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<td>Dislike</td>
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<td>3.70 (.89)</td>
<td>2.20 (.89)</td>
<td>3.62 (.89)</td>
<td>2.20 (.89)</td>
<td>2.84 (.89)</td>
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<tr>
<td></td>
<td>2.84 (.89)</td>
<td>2.98 (.89)</td>
<td>2.24 (.89)</td>
<td>2.24 (.89)</td>
<td>2.98 (.89)</td>
<td>3.68 (.89)</td>
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<tr>
<td>Anger</td>
<td>4.38 (.63)</td>
<td>5.86 (.63)</td>
<td>2.31 (.63)</td>
<td>3.30 (.63)</td>
<td>2.43 (.63)</td>
<td>3.50 (.63)</td>
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<td>1.43 (.63)</td>
<td>1.54 (.63)</td>
<td>1.54 (.63)</td>
<td>1.61 (.63)</td>
<td>1.54 (.63)</td>
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<tr>
<td>Sadness</td>
<td>1.94 (.52)</td>
<td>2.07 (.52)</td>
<td>5.00 (.52)</td>
<td>2.20 (.52)</td>
<td>1.90 (.52)</td>
<td>1.84 (.52)</td>
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<tr>
<td></td>
<td>2.22 (.52)</td>
<td>1.51 (.52)</td>
<td>1.23 (.52)</td>
<td>1.23 (.52)</td>
<td>1.22 (.52)</td>
<td>1.22 (.52)</td>
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</tr>
<tr>
<td>Worry</td>
<td>1.80 (.41)</td>
<td>2.01 (.41)</td>
<td>5.92 (.41)</td>
<td>2.15 (.41)</td>
<td>1.95 (.41)</td>
<td>1.84 (.41)</td>
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<tr>
<td></td>
<td>1.23 (.41)</td>
<td>1.25 (.41)</td>
<td>1.23 (.41)</td>
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<td>1.19 (.41)</td>
<td>1.20 (.41)</td>
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</tr>
<tr>
<td>Embarrassment</td>
<td>1.78 (.31)</td>
<td>1.65 (.31)</td>
<td>1.69 (.31)</td>
<td>5.84 (.31)</td>
<td>1.69 (.31)</td>
<td>6.33 (.31)</td>
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<td>.00</td>
<td>.00</td>
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<td></td>
</tr>
<tr>
<td>Discontent</td>
<td>3.54 (.21)</td>
<td>4.02 (.21)</td>
<td>3.12 (.21)</td>
<td>2.67 (.21)</td>
<td>6.33 (.21)</td>
<td>4.02 (.21)</td>
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<td></td>
<td>1.43 (1.43)</td>
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<td>.00</td>
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</tbody>
</table>

T-test statistics of the experienced emotions are performed within each recalled emotion condition. Bold values are the highest experienced emotion condition coefficients in the corresponding recalled emotion condition.

role of negative emotions. Consequently, a step-down analysis was employed using MANOVA (Bagozzi & Yi, 1989; Bagozzi, Yi, & Singht, 1991). Two groups were created for each recalled emotion condition: group 1 corresponded exclusively to the specific condition, while group 2 included all other conditions. Table 9 summarizes the results of this analysis. Step 1 was a regular MANOVA, with experienced emotion and negative behavioral responses as dependent variables. The results show that recall instructions have a significant effect on these variables. In step 2, the negative behavioral responses were the dependent variables, with the specific emotion used as a covariate. For example, for the dislike condition, in step 1, an omnibus test rejected equal means for all of the negative behavioral responses (comparing, F = 11.25, p < .001; negative word of mouth, F = 48.77, p < .001; switching, F = 28.64, p < .001); therefore, they were tested with the variance due to the remaining dependent variable (e.g., experienced dislike) partitioned out as a covariate. In step 2, a non-significant omnibus test signaled that the negative behavioral responses do not significantly differ across groups after controlling for the specific experienced negative emotion (comparing, F = .24, p = .62; negative word of mouth, F = .270, p = .10; switching, F = .17, p = .68). Therefore, the differences in behavioral responses are wholly due to their functional relations with the specific emotions considered.

The results are largely consistent with our expectations because all of the effects we predicted were significant. In addition, the results indicated a further influence that was not anticipated. In the first stage of the worry condition's step-down analysis, the omnibus test indicated that the rejection of equal means was not possible regarding complaining (F = 1.40, p = .24) and negative word of mouth (F = 2.68; p = .10); therefore, these behavioral responses were not

10 Situations in which the recalled instructions are still significant for some behavioral responses after controlling for the indirect effect through the specific experienced emotion (e.g., negative word of mouth in the case of experienced anger) can be explained in at least two ways. A first one is that the recall conditions may simply have an automatic direct effect on behavioral responses. However, this explanation is unlikely to be correct because such an effect would be difficult to explain without affecting mediation, especially because appraisal can be unconscious (Frijda, 1986; 1993; Lazarus, 1991; Scherer, 1984, 1993). A second and more plausible explanation is that the specific experienced emotion may indeed be a partial mediator of the outcomes and that there may be additional mediators (e.g., other experienced negative emotions that can co-occur) that were not assessed in the present analysis (Zhao, Lynch & Chen, 2010). These additional mediators may contribute to the measured outcomes.
The higher behavioral response is indicated with (a). ANOVAs were performed on each behavioral response among the different recalled emotion conditions. The means with different subscripts differ significantly (Tukey post-hoc test). The higher behavioral response is indicated with (a).

considered in step 2. Furthermore, the difference in switching was entirely due to the effect of the experienced emotion of worry (F = .01, p = .94). In the anger condition, the difference in complaining was entirely due to the specific effect of anger (F = 2.59, p = .11), and the same relation was observed in a negative direction in the embarrassment condition (F = 2.54, p = .11). In the case of the dislike condition, the difference between all three negative consumer behavioral responses to brands – complaining, negative word of mouth, and switching – was due to the functional relationships between these forms of behavior and dislike (complaining, F = .24, p = .62; negative word of mouth, F = 2.70, p = .10; switching, F = 1.7, p = .68). Here, in addition to demonstrating the predicted influences on switching and negative word of mouth, dislike also appeared to be related to complaining. Because dislike involves an expression of disapproval, this relation appears to be consistent. Finally, in both the sadness and the discontent conditions, these emotions were not regarded as wholly affecting any differences in behaviors.

Table 8
Study 5 – means of the measures used to assess predictive validity.

<table>
<thead>
<tr>
<th>Behavioral responses</th>
<th>F-value, p</th>
<th>Effect size</th>
<th>Recalled emotion conditions (mean, SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complaining</td>
<td>F(5, 1208) = 17.16, p = .001</td>
<td>.17</td>
<td>Dislike: 1.65a (1.29), Anger: 2.11a (1.61), Sadness: 1.18b (.78), Worry: 1.47b (1.05), Embarrassment: 1.16b (0.55), Discontent: 1.70b (1.37)</td>
</tr>
<tr>
<td>Negative WOM</td>
<td>F(5, 1207) = 65.63, p = .001</td>
<td>.21</td>
<td>Dislike: 5.50a (1.75), Anger: 5.18a (1.86), Sadness: 2.57a (2.05), Worry: 4.45b (2.11), Embarrassment: 3.12b (2.04), Discontent: 4.58b (1.89)</td>
</tr>
<tr>
<td>Switching</td>
<td>F(5, 875) = 41.20, p = .001</td>
<td>.19</td>
<td>Dislike: 5.87a (1.54), Anger: 5.24a (1.92), Sadness: 2.91b (2.12), Worry: 5.16b (1.97), Embarrassment: 3.56c (2.30), Discontent: 5.44a (1.86)</td>
</tr>
</tbody>
</table>

ANOVA was performed on each behavioral response among the different recalled emotion conditions. The means with different subscripts differ significantly (Tukey post-hoc test). The higher behavioral response is indicated with (a).

Table 9
Study 5 – step-down analyses.

<table>
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<tr>
<th>Dependent variable</th>
<th>F-value</th>
<th>p</th>
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<tr>
<td>Step 1</td>
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<tr>
<td>Complaining</td>
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<td>Negative WOM</td>
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<td>Covariate: experienced dislike</td>
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<tr>
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<tr>
<td>Switching</td>
<td>12.96</td>
<td>.00</td>
</tr>
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</table>

Within worry and discontent conditions, complaining and negative word of mouth were removed from the analyses in step 2.

6.3. Discussion

The pattern of the relations is largely consistent with our general expectation that specific negative emotions could affect specific behavioral outcomes related to brands in different ways. All of the predicted influences for specific emotions were confirmed by the data, while an additional unanticipated influence that emerged from the analysis did not prove problematic in light of our general assertion concerning the relation between emotions and specific actions.

The study confirms the inactive nature of sadness, which has been noted in previous research (Izard & Ackerman, 2000; Mattsson et al., 2004; Shaver et al., 1987). Feeling sad about brands leads consumers to talk very little, if at all, about their experience, and they make no effort to improve their circumstances or to re-establish a positive relationship with the brand. A similar inactive response is observed for discontent, confirming results from previous marketing research (Bougie et al., 2003). Worry primarily leads to brand switching, whereas anger elicits a contrary reaction and induces complaining. Consistent with previous related consumer research, our results reveal that the active nature of anger makes it an apt antecedent of complaining behavior. As demonstrated by, among others, Folkes, Koletsky, and Graham (1987), Casado-Diaz and Mas-Ruiz (2002), and Bougie et al. (2003), anger is often present in a complaint situation when responsibility for a failure can be attributed to a company, particularly regarding factors that the company can control. However, unlike previous research, our study found no evidence that negative word of mouth is wholly due to anger. With regard to embarrassment, it is interesting to observe that this specific emotion implies passivity in consumers, somewhat similar to sadness. Furthermore, the reduced complaining compared to the other emotions is wholly due to its relation with embarrassment. We can therefore affirm that embarrassment inhibits complaining. Lastly, dislike motivates action (Storm & Storm, 1987), and in the presence of dislike toward brands, it is apparent that consumers are oriented toward different possible forms of negative behavior toward the brands.
7. General discussion

Negative emotions play an important role in consumers’ relationships with brands. We developed an 18-item NEB scale that represents the range of negative emotions consumers most frequently experience toward brands. The set of derived emotions can be broken down into six negative emotions (anger, dislike, embarrassment, worry, sadness, and discontent), which various brands evoke differently. The NEB scale proved to be consistent internally as well as across samples and studies; the convergent and discriminant validity was demonstrated by using the MTMM matrix analysis and by comparing other relevant measures available in the marketing and consumer behavior literature. In addition, we demonstrated that the new scale provides superior insights and better predictions than the CES scale and other extant scales do. Lastly, the evidence showed that, consistent with theory, diverse negative emotions toward brands lead to different behavioral consequences. The results of study 5 indicate that focusing on distinctive emotions increases insight into consumers’ behavior when they are exposed to brands that elicit negative feelings. Recent studies (Bonifield & Cole, 2007; Bougie et al., 2003; Nyer, 1997; Sosic, 2007; Zeelenberg & Pieters, 2004) reveal that specific negative emotions have differential effects on customer behavioral responses to service failures. We were able to confirm and extend these findings by revealing the distinctive effects of six negative emotions on consumer responses to brands. In particular, and in line with previous research, we demonstrated the inactive nature of both sadness and discontent and the positive relationship between anger and complaining. Further, our examination of worry, embarrassment, and dislike toward brands revealed new, interesting evidence for brand-related research as well as an understanding of the differential roles that specific negative emotions play. Worry about a brand is positively associated with switching. This finding is in line with basic research in the field of psychology (among others, see Frijda et al., 1989; Roseman et al., 1994) because this type of behavior is similar to those action tendencies naturally induced by emotional feelings clustered under the label of fear, such as escaping, evading, and seeking safety from a potential threat. We also demonstrated the inhibiting effect of embarrassment on customer complaining and/or a general failure to take any form of action other than avoidance. This effect can be explained by the fact that individuals usually feel embarrassed by their behavior, not by a brand (Storm & Storm, 1987). Consequently, although negative actions against brands are less likely in this case, different types of remedial actions aimed at maintaining or restoring a desired personal or social identity without involving the brand’s substitution could well emerge. For example, as also reported in a qualitative study by Grant and Walsh (2009) on brand-related embarrassment, a number of respondents described how they had covered up, removed, or concealed brand logos to avoid potential embarrassment.

Finally, the emotion response of dislike merits particular attention. Dislike is a negative affective reaction to brands based on evaluations of unappealingness, which are, in turn, dependent on personal attitudes and tastes (Ortony et al., 1988). Despite having received little attention in previous marketing or consumer behavior research, dislike can activate consumers, leading to various types of possible negative behavioral responses to brands. In sum, given their different effects on consumers’ behavioral responses, our results confirm the importance of focusing on specific emotions and, more generally, demonstrate that negative emotions play an incontrovertible role in influencing consumers’ actions.

7.1. Managerial implications

This research has practical relevance for marketing and brand managers confronted with the difficulties of managing their brands. Specifically, this research may assist in several specific domains. The NEB scale identifies specific negative emotions toward brands, thus providing a brand-specific tool for assessment and tracking purposes; it is also valuable in terms of predictive validity. That is, practitioners can use it to examine behaviors arising from brand-evoked negative emotions. In the event that these forms of behavior warrant consideration, the results of the scale used can be valuable for developing appropriate countermeasures. For example, our results, consistent with previous research (for an extensive review, see Bonfier, 2010), demonstrate that consumers are generally more likely to switch to other brands or engage in negative word of mouth than they are to seek redress by filing a complaint. Because it does not give the parent company the opportunity to address the problem, this consumer tendency may be detrimental to sales and profits, thus necessitating remedial actions by the parent company. The social sharing of experiences in new media settings is exemplary in this regard. Although it is difficult for managers to address all negative consumer sentiments, our results suggest that it may be more important to address certain types of negative emotions and their antecedents because they are more likely to be shared.

Moreover, companies could use this scale to assess consumers’ negative emotions toward competitive brands. By identifying competing brands that could be used as “enemies” (e.g., Japanese motorcycle brands vs. the Italian manufacturer Ducati), a company could provide its customers with important new components of its brand. In addition, the company could use these components as important elements for oppositional brand loyalty (Muniz & O’Guinn, 2001; Thompson & Sinha, 2008), thus reducing the likelihood that its customers will purchase products from competing brands.

7.2. Research limitations and further research

These results must be tempered by a number of caveats. First, one limitation of this study is its reliance on self-reported measures of emotions and behaviors, which may restrict the conclusions that can be drawn from the findings. Although supportive evidence for actions was found in both studies 4 and 5, it is important that differences in behavior between the emotions constituting the NEB scale be clearly and directly observed in the future. Second, although our findings imply that specific negative emotions affect consumers’ behavioral responses toward brands, our results do not imply that these emotions are the only drivers of such reactions. Evaluative judgments related to brands’ and/or consumers’ individual characteristics and personalities could also play an important role in causing negative outcomes (e.g., Soderlund & Rosengren, 2007, on word of mouth).

We would welcome extensions of the present studies that examine the stability and validity of the NEB scale across cultures. We also recommend that future research examine the scale’s ability to predict behavioral responses that were not investigated here. In particular, based on our research, we expect that, given the active nature of dislike and anger, these emotions affect the forms of protest used against brands, such as boycotting or anti-brand protests on web sites. Likewise, given the social nature of brands, we expect embarrassment to lead to the propensity to refrain from displaying certain brands in public. Furthermore, it would be interesting to determine whether specific negative emotions in the NEB scale are related to the dimensions of brand personality (Aaker, 1997), which, if true, would make the identification of such dimensions very closely connected and relevant. In addition to future work utilizing the NEB scale, we recommend further research on the experiential dimension of specific negative emotions and the antecedent states related to brands. For instance, it would be useful to understand what it means to feel angry with or sad about brands and to identify the conditions that create these emotions. Research by emotion theorists (Ben-Ze’ev, 2000; Ortony et al., 1988) may serve as a useful starting point. Finally, additional studies could examine both negative and
positive emotions. In particular, it could prove interesting to investigate the concept of emotional ambivalence when a consumer experiences both kinds of emotions toward certain brands. What happens in these situations? Which of the polarized emotions most influences behavior? Could the strongest emotion cancel out the effects of any other emotion, or is it simply prioritized in terms of action, with the less intense emotions influencing behavior at a later date? An exploration of these issues could extend our understanding of negative emotions toward brands.

Acknowledgments

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References


An analysis of the profitability of fee-based compensation plans for search engine marketing

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A B S T R A C T

Many advertisers hire agencies to run their search engine marketing campaigns; increasingly, they use innovative performance-based compensation plans. In these plans, the advertiser pays the agency a fee for each conversion (i.e., acquired customer) but requires the agency to pay all of the search engine marketing costs. In this article, the authors address compensation decision problems for search engine marketing for the first time and conclude that such fee-based plans lower the advertiser’s profit by as much as 26–30%. This article uses a simulation study and four empirical data sets to better understand what drives this profit loss. Two causes account for the loss: first, the agency spends less on advertising than is optimal for the advertiser. Second, the agency often earns more to manage the advertiser’s campaign than its minimum requirement. This higher profit for the agency occurs because the advertiser pays the agency more in order to limit the agency’s potential underspending on advertising. The authors show that this latter reason accounts for more than one-third of the advertiser’s profit loss. This article also offers insights into how the advertiser’s profit changes if the advertiser is uncertain about its profit per conversion or if the advertiser does not truthfully reveal its profit per conversion to the agency.

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1. Introduction

Between 2000 and 2010, the number of Internet users worldwide more than quadrupled, from fewer than half a billion to 1.9 billion (Internet World Stats, 2010). Approximately 85% of Internet users have bought at least one product online, and search engines supported 37% of their purchase decisions (Global Nielsen Consumer Report, 2008). Search engine marketing (SEM) has thus become the most important online marketing instrument (Ghose & Yang, 2009). In 2010, SEM constituted 46% of total worldwide online advertising spending, and U.S. advertisers alone spent $12 billion on SEM (IAB, 2011). A major reason for the popularity of SEM is its unique ability to customize an ad to the keyword for the consumer’s search. This customization enables advertisers to attract highly qualified visitors, already interested in buying, to their Web sites (Ghose & Yang, 2009).

The mechanism supporting SEM works as follows (Skiera & Abou Nabout, 2011): a consumer types a keyword, such as “cruise vacation,” into a search engine (e.g., Google) and receives two types of results (see Fig. 1). The lower, left-hand part of the screen shows unsponsored search results, the ranking of which reflects the search algorithm assigned relevance. The top and right-hand sides display sponsored search results. The display of the unsponsored search results is free of charge, whereas the ads that appear among the sponsored search results are paid for by the advertisers each time a consumer clicks on one (Yao & Mela, 2008). For the sponsored search ads, the rankings and prices paid per click are determined by keyword auctions—generalized, second-price, sealed bid auctions (Edelman, Ostrovsky, & Schwarz, 2007; Varian, 2007). Advertisers submit bids for a specific keyword such as “cruise vacation” by stating the maximum amount they are willing to pay for a click (Edelman & Ostrovsky, 2007). The search engine provider weights the submitted bids according to the advertisement’s quality, measured by a proprietary quality score (QS), and ranks the ads accordingly (Abou Nabout & Skiera, 2011). When a user enters a particular keyword into a search engine, the sponsored search results display in decreasing order of the weighted bids (i.e., the product of bids and their quality scores); the ad with the highest weighted bid appears at the top (i.e., first rank, \( x = 1 \)), the ad with the next highest weighted bid is in the second rank \( (x = 2) \), and so on. If a user clicks on an ad at rank \( x \), the corresponding advertiser pays the search engine provider an amount equal to the next highest weighted bid, that is, the weighted bid offered by the advertiser at rank \( x + 1 \), divided by its own quality score. The user who clicked on the ad is then redirected to the

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advertiser’s Web site to place an order or to request a sales quote—in both cases, a potential conversion.

Because consumers use different keywords and combinations of keywords to search for products, typical SEM campaigns contain hundreds to thousands of keywords (Yao & Mela, 2008). As a consequence, advertisers rarely manage SEM campaigns themselves but hire and compensate a dedicated agency to run the campaigns. This agency submits a bid on the price of each ad click, and this bid determines the resulting ad ranks; the ranks in turn influence the number of clicks and, finally, the number of conversions (i.e., acquired customers). Prices per click vary substantially across ranks and can easily jump higher than $1, so the agency's bidding behavior has huge profit implications for the advertiser. Therefore, it is essential to analyze the influence of the advertiser’s compensation plan on the agency’s bidding behavior and profit.

2. Research context

Despite increasing academic interest in SEM (for recent reviews, see Chen, Liu, & Whinston, 2009; Ghose & Yang, 2009; Skiera, Eckert, & Hinz, 2010), no optimal compensation plan for online agencies exists. We know a little more about how to design compensation plans for traditional advertising agencies (Horsky, 2006). Beals and Beals (2001) distinguish three kinds of compensation plans (see also Horsky, 2006): (1) labor-based, using a fee per hour; (2) billing-based, or a percentage commission on media spending; and (3) performance-based, which is based on increases in unit sales or changes in audience attitudes and perceptions where the payments often take the form of supplemental fees. In the past, according to Calantone and Drury (1979), billing-based plans that charged a percentage commission (often 15% of media spending) were very popular, although there were opportunities to better align the objectives of the advertiser and the agency. LaBahn (1996) and Segev (1992) state that advertisers commonly criticize billing-based compensation plans because they lack appropriate incentives for agencies, Spake, D’Souza, Crutchfield, and Morgan (1999) and Horsky (2006) further claim that both billing- and labor-based plans motivate agencies to overspend their media budgets and to overbill advertisers.

Thus, performance-based compensation plans have gained attention from advertisers (Spake et al., 1999; Zhao, 2005), particularly those advertisers involved in online marketing, because the Internet’s digital environment makes it easy to track the number of times an ad appears and the resulting clicks and conversions. A survey of 25 German SEM agencies shows that 82% receive at least some of their compensation on a performance basis (Munkelt, 2007), such as through plans that pay a fee per conversion (Levin, 2006; Reuters, 2009). This fee per conversion must cover both the cost per conversion for the SEM and the agency's profit. Some agencies, such as iProspect Inc. and Zeltraffic, even advertise their SEM services by emphasizing that with their compensation plan, advertisers pay only for the agency's performance.

Fee-based compensation plans do not give advertising agencies an incentive to overspend on advertising—the main issue with the “15% commission plan.” However, they do give agencies an incentive to underspend. Imagine a bank, whose customers potentially are worth $500 each (i.e., profit per conversion = $500). With a fee-based compensation plan, the bank pays its agency (e.g., $50) for each customer (i.e., conversion) that the agency acquires through SEM. The $50 fee limits the amount of money that the agency will spend to acquire new customers. For the agency, the situation is similar to one in which the bank acquires customers who are worth only $50. The agency thus tends to underspend and submits lower bids than the bank would prefer. This scenario leads to lower acquisition costs per customer and less spent on advertising, but it also results in less attractive rankings for the ads, fewer clicks, and fewer acquired customers. If we assume that the agency spends less than the advertiser would, the crucial question is then how severe are the consequences for the advertiser’s profitability?

Conceptually, this problem is similar to the price delegation problem in sales force management, when sales representatives influence the firm’s profitability by setting the prices and thus affecting their sales. A sales representative who receives a percentage commission on unit sales generally has an incentive to lower prices, because a price decrease often enhances sales (which is good for the sales
representative). However, this move has little appeal for the firm, which will thereby earn lower profits (bad for the firm). Weinberg (1975) proposes instead aligning firm and sales representative interests by requiring the firm to share its profit with the sales representative.

Such incentive-compatible compensation plans provide many well-documented advantages (Coughlan, 1993; Coughlan & Sen, 1989; Farley, 1964); but how significantly does profit decrease when compensation plans are not incentive compatible? Previous studies have used analytical models to identify the determinants of profit differences for firms and sales representatives, without focusing on the exact size of the differences (Albers, 2002). This lack of knowledge might explain why advertisers still favor non-incentive-compatible (i.e., fee-based) compensation plans. More knowledge about the magnitude of the profit decreases for advertisers should increase their caution in using such plans.

Therefore, we investigate when, why, and how strongly fee-based compensation plans lower an advertiser's profit. To do so, we compare the profitability of the fee-based plan with the profitability of another performance-based compensation plan that is incentive compatible and relies on the idea of shared profits (Weinberg, 1975). We also analyze the impacts of uncertainty regarding the profit per conversion and the advertiser's unwillingness to reveal its true profit per conversion on profitability.

### 3. Performance-based compensation plans in search engine marketing

In this section, we present two performance-based compensation plans: (1) the commonly used fee-based compensation plan and (2) an incentive rate-based compensation plan that is incentive compatible and based on the idea of shared profits (Weinberg, 1975). We assume that both the advertiser and the agency are risk neutral, which greatly facilitates our analysis but is also reasonable because both firms are involved in many different activities.

#### 3.1. Fee-based compensation plan

Under the fee-based compensation plan, the advertiser pays the agency a fee per conversion \( m \), which is part of the advertiser's profit per conversion for keyword \( k \), \( p_k \). The agency must pay all costs for SEM, including running the campaign and placing the ads. These latter costs equal the prices per click that the search engine provider charges. An SEM campaign contains \( k \) different keywords (frequently ranging from hundreds to thousands) that differ in their prices per click at rank one \( b_k \), their clickthrough rates at rank one \( ctr_k \), and their conversion rates \( cr_k \). They also vary within ranks in terms of their percentage increases in prices per click \( \delta_k \) and clickthrough rates \( \xi_k \). We summarize all of these variables in Table 1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>( k )</td>
<td>Keyword subscript</td>
</tr>
</tbody>
</table>

Depending on the fee per conversion, the agency submits auction bids for each keyword, and the bid determines the clicks and conversions for the advertiser. The fee-based compensation plan thus entails two optimization problems: (1) optimizing the agency's bidding decision and (2) optimizing the advertiser's compensation decision.

#### 3.1.1. Agency's bidding decision problem

With fee-based compensation (FB), the risk-neutral agency (AG) attempts to maximize its profit after SEM costs for the entire SEM campaign \( \pi^{FB} \) by making a decision about the bid \( b_k^{FB} \) for each keyword \( k \), which also depends on the advertiser's fee per conversion \( m \). This bid determines the rank of the ad in the sponsored search results, the clickthrough rate, the number of clicks, the SEM costs per conversion, \( g_k^{FB} \), and the number of conversions per keyword in the SEM campaign, \( s_k^{FB} \). Together with the advertiser's fee per conversion, the SEM costs per conversion, and the number of conversions, the bid per keyword determines the agency's profit after SEM costs (see Eq. (1a)). Higher bids usually lead to higher prices per click and better ranks in the sponsored search results, prompting greater awareness, more clicks, and more conversions; these results lead to higher SEM costs per conversion. Therefore, the agency trades off between the number of conversions and the SEM costs per conversion by solving the following bidding decision problem:

\[
\max_{b_k^{FB}} \pi^{FB}(b_k^{FB} (m)) = \sum_{k \in K} (m - g_k^{FB} (b_k^{FB} (m))) \cdot s_k^{FB} (b_k^{FB} (m)) \tag{1a}
\]

subject to

\[
0 \leq b_k^{FB} \leq b_1. \tag{1b}
\]

The number of conversions \( s_k^{FB} \) is the product of the number of users searching for the keyword \( n_k \) times the conversion rate \( cr_k \) times the clickthrough rate \( ctr_k \):

\[
s_k^{FB} = n_k \cdot ctr_k \cdot cr_k. \tag{1c}
\]

The SEM costs per conversion are the SEM costs per keyword, equal to the number of clicks times the price per click, divided by the number of conversions. Following Ghose and Yang (2009), we approximate the price per click with the bid, because the difference between the bid and the price is small in a competitive market and should not provide any particular advantage for a specific compensation plan. (In Appendix A, we confirm this claim with the results of an

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Table with description of variables.</th>
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<tr>
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<tr>
<td>( k )</td>
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<td>( b_k )</td>
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<td>Clickthrough rate at rank one of keyword ( k )</td>
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<tr>
<td>( cr_k )</td>
<td>Conversion rate of keyword ( k )</td>
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<tr>
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</tr>
<tr>
<td>( c )</td>
<td>Incentive rate</td>
</tr>
<tr>
<td>( b_k^{FB} )</td>
<td>Bid for keyword ( k )</td>
</tr>
</tbody>
</table>

Notes: FB = fee-based compensation plan, IRB = incentive rate-based compensation plan.

\( \pi \)Advertiser’s profit after SEM costs for the entire SEM campaign

\( \xi \)SEM costs per conversion for keyword \( k \)

\( \delta \)Number of conversions for keyword \( k \)

\( \xi \)Agency’s profit after SEM costs for the entire SEM campaign

\( m \)Campaign

\( c \)Equal to the number of clicks times the price per click, divided by the number of conversions, following Ghose and Yang (2009).
empirical study of the differences between bids and prices paid for 364 keywords in 14 industries at up to three points in time.) Thus, the SEM costs per conversion $g_k^{IRB}$ are the ratio of the agency’s bid $b_k^{IRB}$ to the conversion rate $c_{rk}$:

$$g_k^{IRB} = \frac{b_k^{IRB}}{c_{rk}}. \quad (1d)$$

The clickthrough rate $c_{rk}$ depends on the rank of the ad, which in turn depends on the bid per keyword $b_k^{IRB}$, the clickthrough rate at rank one ($c_{r1}$), and the percentage increase in the clickthrough rate from rank $x + 1$ to rank $x$ ($\delta_x$). Because the clickthrough rate is positive and increases exponentially within decreasing ranks (Feng, Bhargava, & Pennock, 2007), we model it as follows:

$$c_{rk} = \frac{c_{r1} \delta_x^{(x-1)}}{\delta_x}. \quad (1e)$$

The price per click depends on the price per click at rank one ($b_1$) and the percentage increase in prices per click from rank $x + 1$ to rank $x$ ($\delta_x$). The price per click must be positive and increase exponentially as the rank decreases (Ganchev et al., 2007):

$$b_k^{IRB} = \frac{b_1}{\left(\delta_x^{(x-1)}\right)}. \quad (1f)$$

The rank function is an inversion of this price function:

$$r_k^{IRB} = 1 - \frac{\ln\left(b_k^{IRB} / b_1\right)}{\ln(b_1)}. \quad (1g)$$

Because each keyword $k$ is characterized by the price per click at rank one and the percentage increase in prices per click from rank $x + 1$ to rank $x$ (see Eq. (1f)), the agency needs to decide how to place the advertiser’s bid at the appropriate rank for a given keyword such that it maximizes the objective function described in Eq. (1a).

Therefore, the agency’s optimal SEM costs per conversion $g_k^{IRB}$ and the number of conversions $s_k^{IRB}$ are:

$$g_k^{IRB}^{**} = \begin{cases} \frac{m \cdot \xi_k'}{\delta_k + \xi_k'} & \text{if } b_k^{IRB} < b_1^1, \\ b_1^1, & \text{if } b_k^{IRB} \geq b_1^1. \end{cases} \quad (2b)$$

$$s_k^{IRB}^{**} = \begin{cases} n_k \cdot c_{rk} \cdot r_k^{IRB} \cdot \left(\frac{m \cdot \xi_k'}{b_1^1 \cdot (\delta_k + \xi_k')}\right), & \text{if } b_k^{IRB} < b_1, \\ n_k \cdot c_{rk} \cdot r_k^{IRB}, & \text{if } b_k^{IRB} \geq b_1. \end{cases} \quad (2c)$$

3.1.2. Advertiser’s compensation decision problem

The risk-neutral advertiser considers the effect of its fee per conversion $m$ on the agency’s bidding behavior according to Eq. (2a). It also should take into account the agency’s minimum profit after SEM costs $m_{min}$, which is the minimum amount of money the agency will require to manage the advertiser’s SEM campaign. Thus, the advertiser maximizes its profit for the SEM by determining an optimal fee per conversion that covers the costs for the agency:

Maximize $\omega_k^{IRB}(m) = \sum_{k \in K} (p_k - m) \cdot s_k^{IRB}(b_k^{IRB}(m))$, subject to

$$\sum_{k \in K} (m - b_k^{IRB}(b_k^{IRB})) \cdot s_k^{IRB}(b_k^{IRB}) \geq m_{min}. \quad (3b)$$

Subjecting the agency’s optimal bidding behavior from Eqs. (2a)–(2c) into Eqs. (3a) and (3b), we derive the advertiser’s compensation decision problem under the fee-based compensation plan (with the restriction that the rank cannot be better than rank one, and the bid cannot be higher than the bid for rank one):

Maximize $\omega_k^{IRB}(m) = \sum_{k \in K} (p_k - m) \cdot n_k \cdot c_{rk} \cdot r_k^{IRB} \cdot \left(\frac{m \cdot \xi_k'}{b_1^1 \cdot (\delta_k + \xi_k')}\right)$, subject to

$$\sum_{k \in K} \left( m - \frac{m \cdot \xi_k'}{b_1^1 \cdot (\delta_k + \xi_k')} \right) \cdot n_k \cdot c_{rk} \cdot r_k^{IRB} \cdot \left(\frac{m \cdot \xi_k'}{b_1^1 \cdot (\delta_k + \xi_k')}\right) \geq m_{min}. \quad (3d)$$

Although a closed-form solution for the optimal fee for the whole campaign $m^{**}$ does not exist, a heuristic like the Newton search method offers an easy solution to this optimization problem.

3.2. Incentive rate-based compensation plan

Another performance-based compensation plan employs the idea of shared profits (Weinberg, 1975) and can serve as a benchmark for analyzing the profitability of a fee-based compensation arrangement. Under this incentive rate-based compensation plan (IRB), the risk-neutral agency receives an incentive rate $c$ for each keyword $k$ in the SEM campaign that equals a percentage of the risk-neutral advertiser’s profit after SEM costs $\omega_k^{IRB}$. The agency submits bids $b_k^{IRB}$, considering the incentive rate $c$ for each keyword $k$ in the SEM campaign to maximize its profit after SEM costs $\omega_k^{IRB}$. The profit consists of the sum of profits after the SEM costs of all keywords, which equals the product of the incentive rate $c$ times the difference between the profit per conversion $p_i$ and the SEM costs per conversion $g_i^{IRB}$ times the number of conversions $s_k^{IRB}$.
The advertiser maximizes the profit after SEM costs, multiplied by \((1 - c)\), by determining the optimal incentive rate \(c^*\) for the entire campaign, which ensures that the agency earns at least its minimum required profit \(n^\text{min}\). Consequently, both parties aim to maximize the profit after the SEM costs per campaign, and incentive compatibility exists. The advertiser's compensation decision problem with this incentive rate-based compensation plan is as follows:

\[
\text{Maximize } \pi_{IRB}^R(c) = (1 - c) \cdot \sum_{k = K} (p_k - b_k^{IRB} \cdot (b_k^{IRB}/b_k^{IRB})) \cdot \omega_k \cdot (b_k^{IRB}/b_k^{IRB}), \quad (4a)
\]

subject to

\[
c \cdot \sum_{k = K} (p_k - b_k^{IRB} \cdot (b_k^{IRB}/b_k^{IRB})) \cdot \omega_k \cdot (b_k^{IRB}/b_k^{IRB}) \geq n^\text{min}, \quad (4b)
\]

\[
0 \leq b_k^{IRB} \leq b_k^1, \quad (4c)
\]

Because the incentive rate in the advertiser's profit function (Eq. (4a)) must be as small as possible and the constraint for the minimum agency profit (Eq. (4b)) encourages the incentive rate to be as high as possible, the constraint (4b) is always binding. Solving the corresponding system of Kuhn–Tucker optimality conditions yields the agency's optimal bid per keyword:

\[
b_k^{IRB} = \frac{p_k \cdot c r_k \cdot \omega_k^c}{\bar{b}_k^1 + \omega_k^c \cdot \bar{b}_k^1}, \quad \text{if } b_k^{IRB} < b_k^1,
\]

\[
\frac{n^\text{min} \cdot \sum_{k = K} p_k \cdot c r_k \cdot \omega_k^c}{\bar{b}_k^1 \cdot (\bar{b}_k^1 + \omega_k^c)} \cdot \frac{\bar{b}_k^1}{\bar{b}_k^1} - \frac{c r_k \cdot \omega_k^c}{\bar{b}_k^1 \cdot (\bar{b}_k^1 + \omega_k^c)} \cdot \frac{\bar{b}_k^1}{\bar{b}_k^1}, \quad \text{if } b_k^{IRB} \geq b_k^1,
\]

as well as the advertiser's optimal incentive rate:

\[
c^* = \begin{cases} 
\frac{n^\text{min} \cdot \sum_{k = K} p_k \cdot c r_k \cdot \omega_k^c}{\bar{b}_k^1 \cdot (\bar{b}_k^1 + \omega_k^c)}, & \text{if } b_k^{IRB} < b_k^1, \\
\frac{n^\text{min} \cdot \sum_{k = K} p_k \cdot c r_k \cdot \omega_k^c}{\bar{b}_k^1 \cdot (\bar{b}_k^1 + \omega_k^c)} \cdot \frac{\bar{b}_k^1}{\bar{b}_k^1} - \frac{c r_k \cdot \omega_k^c}{\bar{b}_k^1 \cdot (\bar{b}_k^1 + \omega_k^c)} \cdot \frac{\bar{b}_k^1}{\bar{b}_k^1}, & \text{if } b_k^{IRB} \geq b_k^1.
\end{cases}
\]

### 3.3. Numerical example

With a numerical example, we illustrate the advertiser’s optimal fee-based and incentive rate-based compensation plans, according to the stated decision problems in Eqs. (1a) and (1b), (3a) and (3b), and (4a)–(4c). This illustration also establishes the agency's corresponding optimal bidding behavior and the profit consequences for the advertiser and the agency under both compensation plans. In this example (see Table 2), the advertiser's profit per conversion \(p\) is $100, the number of searches \(n\) is 20,000, the price per click at rank one \(b^1\) is $2.00, the percentage increase in prices per click \(g\) is 50%, the clickthrough rate at rank one \(c r^1\) is 6%, the percentage increase in clickthrough rates \(\omega\) is 50%, and the conversion rate \(c v\) is 2%. We discover the advertiser's optimal fee per conversion by maximizing Eqs. (3c) and (3d) with the help of a Newton search method. Eq. (5b) then allows us to calculate the optimal incentive rate \(c^*\). Applying Eqs. (2a) and (5a) reveals the optimal bid for both compensation plans.

In Table 2, we outline the two possible situations and their outcomes according to the fee-based compensation plan and the benchmark incentive rate-based compensation plan. The only difference that we impose is that we have set the agency's minimum profit \(n^\text{min}\) to $150 in Situation 1 and to $100 in Situation 2.

### Situation 1

In Situation 1, the advertiser’s optimal fee per conversion is $50, and the optimal incentive rate is 25%. The agency's optimal bid under the fee-based compensation plan is lower than their optimal bid under the incentive rate-based compensation plan ($50 vs. $1.00), leading to an inferior rank under the fee-based compensation plan (4.42 vs. 2.71). The superior rank with the incentive rate-based compensation plan (2.71) increases the number of conversions (12 vs. 6) but also increases the SEM costs per conversion ($50 vs. $25). The agency's profit after the SEM costs is the same with both plans, at $150 (FB: $150 = ($50 - $25) · 6, IRB: $150 = 25% · ($100 - $50) · 12). However, the advertiser's profit reaches $450 with the incentive rate-based compensation but only $300 with the fee-based compensation. Thus, the difference in the advertiser's profit is driven solely by the difference in the agency's bidding behavior, namely, underbidding by the agency.

In Situation 2, the optimal fee per conversion is still $50, but the optimal incentive rate of 16.67% is lower than the rate in Situation 1. The optimal bids, ranks, numbers of conversions, and SEM costs per conversion do not change. However, the agency's profit after SEM costs now equals only $100 for the incentive rate-based compensation plan ($100 = ($50 - $25) · 6, IRB: $100 = 25% · ($100 - $50) · 12). Furthermore, instead of $450, the advertiser now earns $500 with the incentive rate-based compensation, but the fee-based compensation still leads to an advertiser profit of $300. The difference in the advertiser's profit thus equals $200, and the agency earns $150 instead of $100. Therefore, 25% of the profit difference ($50/ $200) is related to the agency’s profit being higher than the minimum, and 75% ($150/$200) is caused by the agency's underbidding. Thus, in Situation 2, the advertiser's profit is driven by differences in both the agency's bidding behavior and the agency's higher profit.

If we were to restrict the agency's minimum profit \(n^\text{min}\) to $100 under the fee-based compensation plan, the optimal fee would equal $40.82, the agency would spend even less money on SEM, with an optimal bid of $4.11; instead of rank 4.42, the agency would receive rank 4.92, with SEM costs per conversion of $20.41 and only 6 conversions. This bidding behavior would produce a profit of $100 for the agency but a lower profit of only $289.90 for the advertiser (cf. profit of $300 without the above restriction). Thus, our numerical example illustrates why an advertiser might grant an agency a
higher-than-required profit; it also demonstrates how fee-based compensation lowers the advertiser’s profit. We will next examine when and how strongly this profit decrement occurs.

4. Analysis of the profitability of the fee-based compensation plan

To measure the differences in the agency’s bids under the fee- and incentive rate-based compensation plans, we divide Eq. (5a) by Eq. (5b):

$$\Delta b_k = \frac{b_{IRB}^{FB} - b_{IRB}^{BB}}{b_k} = \begin{cases} \frac{m}{p_k} - 1, & \text{if } b_{IRB}^{BB} < b_k^{IRB} \\ 0, & \text{if } b_{IRB}^{BB} \geq b_k^{IRB} \end{cases}$$

(6)

Eq. (6) shows that the bids of the agency under fee-based compensation are always lower than or equal to the bids submitted under the incentive rate-based compensation plan.2 The bids only coincide if the bid under the incentive rate-based compensation plan leads to rank one or if the optimal fee \(m^*\) is equal to the profit per conversion \(p_k\); however, in the latter case, the advertiser does not achieve any profits. Otherwise, the greater the difference between the optimal fee \(m^*\) and the profit per conversion \(p_k\), the more the agency’s bidding behavior deviates from the incentive rate-based compensation plan.

We also measure the percentage deviation in the advertiser’s profit per campaign for the fee-based vs. the incentive rate-based compensation plan, as follows:

$$\Delta \sigma = \frac{\sigma^{IRB} (m^*) - \sigma^{BB} (c)}{\sigma^{BB} (c)}$$

(7)

Unfortunately, we cannot analytically derive the corresponding differences in the advertiser’s profit. Therefore, we use a simulation study and four empirical data sets to examine the profitability of the fee-based compensation plan.

4.1. Simulation study

The advantage of the simulation study is that it covers many different situations; its drawback is that all situations are not equally likely to occur in reality. Thus, the simulation study covers extreme situations and offers insights into extreme results, while the average results might be overly influenced by these extreme situations. Therefore, we subsequently detail the results that firms are most likely to encounter using four empirical data sets obtained from four real-world campaigns.

4.1.1. Design of the simulation study

We initiate our simulation study by using the findings of previous empirical research with our analysis of data from Google’s traffic estimator tool; we use this tool to identify reasonable ranges for the factor levels of the percentage increases in clickthrough rates and prices per click (see Table 3).

For the price per click at rank one, we turn to a German SEM price index published by Explido, which reports 2009 average price per click at rank one of $1.64 for the telecommunications industry and $4.02 for the financial services industry. We thus define a low price per click at rank one \(b_k\) as between $0.50 and $2.75 and a high price as between $2.76 and $5.00. To calculate the percentage increases in prices per click from rank \(x + 1\) to rank \(x\), we use data from Google’s traffic estimator tool (see Appendix B), which suggests that low percentage increases are 10–95% and high percentage increases are 96–180%. This tool also shows that the range of price per click varies between approximately $0.06 (keyword at rank 8, price per click at rank one of $5.00, and 35% decay rate) and $5 (keyword at rank one). These values are consistent with the price per click listed in several empirical studies for ranks between 4 and 7, namely, $2.41 to $3.55 (Ghose & Yang, 2009; Misra, Pinker, & Rimm-Kaufman, 2006; Rutz & Bucklin, 2007, 2011).

Consistent with the findings of previous studies (Agarwal, Hosanagar, & Smith, 2011; Misra et al., 2006; Rutz & Bucklin, 2007), we use conversion rates between 0.5% and 5%. We reproduce bidding scenarios for three categories of industries: high profit per conversion between $251 and $500, as is common for financial services; medium profit per conversion between $51 and $250, such as in the telecommunications industry; and low profit per conversion between $10 and $50, such as for the food industry.

Agarwal et al. (2011) and Misra et al. (2006) find an average click-through rate of 2.41% at an average rank of 5.77 for a fashion retailer and 7.45% at rank 3.56 for the travel industry. Accordingly, we use clickthrough rates between 2% and 5% for the low factor level and between 6% and 10% for the high factor level. For the percentage increases in clickthrough rates, we again rely on data from Google’s traffic estimator tool (see Appendix B), which suggests low percentage increases of 10–90% and high percentage increases of 91–170%. For a constant number of consumers searching for each keyword \(n_k\), these values reflect the heterogeneity in clicks per keyword observed in real-world data.

By randomly drawing ten values from the uniform distributions for all factors, we simulate scenarios for 960 different keywords (Table 3). We order these keywords based on profit per conversion \(p_k\) and thus form 30 campaigns with 32 keywords that indicate high, medium, and low profits per conversion. We use the decision models in Eqs. (3a) and (3b) and (4a)–(4c) to calculate the optimal fee \(m^*\) under the fee-based compensation plan and the optimal incentive rate \(c^*\) for the 30 specified campaigns, respectively. We calculate the minimum required profit for the agency \(m^{min}\) in each campaign as the sum of the prices per click at rank one of all 32 keywords in the campaign, times 2.

4.1.2. Results of simulation study

We first analyze the differences in the profitability earned with the fee-based and incentive rate-based compensation plans. Next, we analyze the causes of these differences. As we show in Table 4, the advertiser pays the agency an average optimal incentive rate \(c^*\) of 22.52% under the incentive rate-based compensation plan, which yields an average advertiser profit of $83,420.72. The average optimal fee per conversion and campaign \(m^*\) is $60.76 under the fee-based plan.
compensation plan, which leads to an average advertiser profit of $61,991.96. This profit is 25.69% lower than the corresponding profit under the incentive rate-based compensation plan.

As we summarize in Situation 2 of our numerical example (Section 3.3), this profit decrease occurs because the agency submits a lower bid in the fee-based compensation plan. The lower bid brings the average SEM cost per conversion 44.76% lower than it would be with the incentive rate-based compensation plan, while the conversions drop by 31.60%. As a result of underbidding, the agency’s profit under the fee-based compensation plan averages $16,024.41, or 66.62% higher than that it earns under the incentive rate-based compensation plan (i.e., $9,617.20). To keep the agency from bidding even lower, the advertiser must provide additional incentives. A higher fee encourages the agency to bid higher, which should increase the number of conversions and thus increase the profit for the advertiser. However, additional incentives are not needed under the incentive rate-based compensation plan, because the agency’s optimal bid (Eq. (4b)) under the fee-based compensation plan is always binding.

From the $21,428.75 difference in the advertiser’s average profit (=$83,420.72 – $61,991.96) between the compensation plans, we can identify the portion attributable to the agency’s higher profit ($6,407.21 = $16,024.41 – $9,617.20) and the portion driven by the difference in bidding behavior ($15,021.54 = $21,428.75 – $6,407.21). Consequently, we calculate that 29.90% (=$6,407.21/$21,428.75) of the profit difference relates to higher agency profit due to underbidding.

A comparison of the bids for the 960 keywords shows that bidding is not profitable for 92 of them (9.58%), a scenario that mimics real-world situations where it is too expensive to bid on keywords. In this case, we can assume that the agency knows that bidding is not profitable and does not bid. Furthermore, for 96 keywords (10.00%), an agency that earns fee-based compensation bids for rank one. Therefore, the bids produced by the two compensation plans are equal for only 188 keywords (19.58%), and for 80.42% of these 960 keywords, the different compensation plans lead to different rankings because the bids are lower under fee-based compensation (see Eq. (6)). These lower bids under the fee-based compensation plan lead to lower profits for the advertiser.

With a more detailed analysis of the results from each of our 30 campaigns, we find that the percentage deviations in the advertiser’s profit vary between -6.04% and -40.35%. In 15 campaigns, the advertiser pays the minimum required profit to the agency (under both compensation plans), so the average deviation of -22.02% in the advertiser’s profit results solely from differences in bidding behavior. For the other 15 campaigns, the average deviation of -26.69% reflects differences in both the agency’s bidding behavior and the agency’s higher profits.

4.2. Influence of uncertainty and false information about profit per conversion

We further examine the performance of both compensation plans in situations where the advertiser (1) is uncertain and, out of ignorance, over- or underestimates the profit per conversion (influence of uncertainty) or (2) knows the profit per conversion exactly but does not want to reveal this information to the agency (influence of false information). The first situation might occur because the advertiser is not fully aware of the profit per conversion, which usually corresponds to the profit per customer. For example, perhaps the advertiser’s information systems cannot determine this value, the advertiser focuses only on the short-term value of customers, or the advertiser makes errors in calculating these values. In the second situation, the advertiser might not want to share information with the agency and thus reveals a false (usually lower) profit per conversion. We analyze the effects of this uncertainty and false information on the advertiser’s profit for the 30 campaigns and the 960 keywords that appear in our simulation study.

4.2.1. Uncertainty about advertiser’s profit per conversion

Uncertainty about the advertiser’s profit per conversion influences bidding behavior under both plans. The agency’s optimal bid (Eq. (5a)) under the incentive rate-based compensation plan depends on the over- or underestimated profit per conversion, $P_k \pm x\%. The agency’s optimal bid (Eq. (2a)) under the fee-based compensation plan depends on the advertiser’s fee, which is again based on the over- or underestimated profit per conversion, $P_k \pm x\%. Therefore, though the advertiser’s profits are always based on the advertiser’s true profit per conversion, $P_k \pm 0\%, the agency’s profits reflect the fee per conversion under the fee-based compensation plan or the (contractually fixed) over- or underestimated profit per conversion for the incentive rate-based compensation plan.

We simulate 12 different levels of over- and underestimation of the advertiser’s profit per conversion for each of the 960 keywords (see Table 5), which we again summarize across the 30 campaigns listed in Table 4. The deviations in profit without uncertainty (Table 5, row ±0%) correspond to the results in Table 4 (.00% and -25.69%). The second and third columns reveal the effect of uncertainty on the degree that the advertiser’s profit deviates from the optimum when $P_k \pm 0\%$. This uncertainty has moderate effects: the profit under the incentive rate-based compensation plan decreases by less than 8%, even when the advertiser underestimates its profit per conversion by over 50%. In the case of an overestimation of 50%, this deviation is even smaller (~1.83%). This finding confirms that underestimating on customer acquisition has severe consequences for the advertiser’s profit after SEM costs, as we earlier determined in our comparison of the fee-based and incentive rate-based compensation plans. The deviations under the fee-based compensation plan are generally comparable: for an over- or underestimation of 50%, profit decreases by 2.40 and 4.62 percentage points, respectively. The profitability of compensation plans is thus barely influenced by uncertainty; including this factor does not change our primary finding that the fee-based compensation plan performs substantially worse than the incentive rate-based compensation plan.

4.2.2. False information about advertiser’s profit per conversion

False information about the advertiser’s profit per conversion only influences the agency’s bidding behavior under the incentive rate-based compensation plan, because the agency’s optimal bid depends

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Table 4
Simulation study results.

<table>
<thead>
<tr>
<th></th>
<th>Incentive rate-based compensation</th>
<th>Fee-based compensation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advertiser’s profit</td>
<td>$83,420.72</td>
<td>$61,991.96</td>
</tr>
<tr>
<td>(% deviation)</td>
<td>(−25.69%)</td>
<td></td>
</tr>
<tr>
<td>Optimal compensation</td>
<td>22.52% of profit*</td>
<td>30.70% per conversion</td>
</tr>
<tr>
<td>Agency’s profit</td>
<td>$9,617.20</td>
<td>$16,024.41</td>
</tr>
<tr>
<td>(% deviation)</td>
<td>(66.62%)</td>
<td></td>
</tr>
<tr>
<td>Number of conversions</td>
<td>517.51</td>
<td>353.90</td>
</tr>
<tr>
<td>(% deviation)</td>
<td>(−31.60%)</td>
<td></td>
</tr>
<tr>
<td>SEM costs</td>
<td>$33,368.16</td>
<td>$13,461.87</td>
</tr>
<tr>
<td>(% deviation)</td>
<td>(−59.68%)</td>
<td></td>
</tr>
<tr>
<td>SEM costs per conversion</td>
<td>$49.63</td>
<td>$27.41</td>
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<tr>
<td>(% deviation)</td>
<td>(−44.76%)</td>
<td></td>
</tr>
<tr>
<td>Difference in advertiser’s profit</td>
<td>./</td>
<td>70.10%</td>
</tr>
<tr>
<td>due to underbidding</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference in advertiser’s profit</td>
<td>./</td>
<td>29.90%</td>
</tr>
<tr>
<td>due to overly high agency profit</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: SEM = search engine marketing.

* Profit refers to search engine marketing.
4.3. Analysis of empirical data sets

Although the simulation study covers many different situations, not all of these situations are equally likely to occur. Therefore, we analyze four empirical data sets pertaining to four SEM campaigns conducted on Google, representing four different industries (fashion, mobile phones, industrial goods, and travel) managed by a German SEM agency from August to December 2007. These data reflect diverse settings: the agency used 306 keywords for the fashion campaign, 1233 for mobile phones, 3035 for industrial goods, and 4204 keywords for the travel campaign.

4.3.1. Descriptive statistics of empirical data sets

In Table 6, we present the descriptive statistics for the prices per click, the ranks, the number of consumers searching for each keyword, the clickthrough rate, the number of conversions, the SEM costs, and the SEM costs per conversion. Although the prices per click are the most expensive in the industrial goods campaign (mean = 0.06€), the SEM costs per conversion are the highest for the mobile phone campaign (mean = 234.51€). This result mainly reflects the extremely low conversion rate (mean = 0.00%) and rather low clickthrough rate (mean = 3.89%) for the mobile phone campaign. Compared with the high number of searches for mobile phones (mean = 49,422.57), there are few searches for travel (mean = 599.07). Yet, the conversion rate (mean = 5.57%) and clickthrough rate (mean = 14.75%) are much higher in the travel campaign, producing very low SEM costs per conversion (mean = 1.82€). The profit per conversion varies between 30€ and 100€, depending on the industry.

Although Google provides advertisers with information on price per click and clickthrough rates for their own campaigns, it does not provide similar information about competitors’ campaigns. Thus, it is difficult to calculate percentage increases in prices per click and clickthrough rates from rank x + 1 to rank x. Instead, we turn to another data source, Google’s traffic estimator tool, to define the ranges for these percentage increases (see Appendix B). With this data source, we can cover a wide range of keywords for the four industries with varying popularity levels. For the estimation, we draw a random number for each keyword from the (uniformly distributed) ranges of increases in prices per click and clickthrough rates. We repeat this process five times and report the average results obtained.

As shown in Table 6, the estimated percentage increases in prices per click vary between 20% and 160% for the fashion industry, 10% and 150% for the mobile phone industry, 40% and 180% for the industrial goods industry, and 10% and 160% for the travel industry. The traffic estimator data also suggest that percentage increases in clickthrough rates vary between 20% and 150% for the fashion industry, 10% and 170% for the mobile phone industry, 15% and 150% for the industrial goods industry, and 20% and 110% for the travel industry.

The agency’s minimum profit after SEM costs also differs across the four campaigns because of the variance in the additional services it delivers to clients (e.g., number of meetings, report details, education of the client’s employees). For an appropriate comparison, we consider three different levels for the agency’s minimum required profit in each of the industries: 1000€, 3000€, and 6000€. For each respective time period, 1000€ is the absolute minimum for managing a campaign (i.e., 1 h per week invested), whereas 6000€ allows the agency to invest more time and fulfill additional client requirements.

### Table 5

<table>
<thead>
<tr>
<th>Over- and underestimation of advertiser’s profit per conversion</th>
<th>Percentage deviation in advertiser’s profit per conversion</th>
<th>Effect of uncertainty in IRB</th>
<th>Effect of uncertainty in FB</th>
<th>Effect of false information on profit difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_k + 50%$</td>
<td>$-1.83%$</td>
<td>$-28.09%$</td>
<td>$-23.85%$</td>
<td>$-25.68%$</td>
</tr>
<tr>
<td>$p_k + 40%$</td>
<td>$-1.31%$</td>
<td>$-27.39%$</td>
<td>$-24.57%$</td>
<td>$-27.05%$</td>
</tr>
<tr>
<td>$p_k + 30%$</td>
<td>$-0.81%$</td>
<td>$-27.05%$</td>
<td>$-24.88%$</td>
<td>$-27.56%$</td>
</tr>
<tr>
<td>$p_k + 20%$</td>
<td>$-0.41%$</td>
<td>$-26.56%$</td>
<td>$-25.28%$</td>
<td>$-25.65%$</td>
</tr>
<tr>
<td>$p_k + 10%$</td>
<td>$-0.03%$</td>
<td>$-25.92%$</td>
<td>$-25.56%$</td>
<td>$-25.66%$</td>
</tr>
<tr>
<td>$p_k + 0%$</td>
<td>$0.00%$</td>
<td>$-25.69%$</td>
<td>$-25.69%$</td>
<td>$-25.69%$</td>
</tr>
<tr>
<td>$p_k - 5%$</td>
<td>$-0.04%$</td>
<td>$-25.72%$</td>
<td>$-25.65%$</td>
<td>$-25.65%$</td>
</tr>
<tr>
<td>$p_k - 10%$</td>
<td>$-0.16%$</td>
<td>$-25.82%$</td>
<td>$-25.52%$</td>
<td>$-25.52%$</td>
</tr>
<tr>
<td>$p_k - 20%$</td>
<td>$-0.88%$</td>
<td>$-26.08%$</td>
<td>$-25.01%$</td>
<td>$-25.01%$</td>
</tr>
<tr>
<td>$p_k - 30%$</td>
<td>$-1.75%$</td>
<td>$-26.90%$</td>
<td>$-23.94%$</td>
<td>$-23.94%$</td>
</tr>
<tr>
<td>$p_k - 40%$</td>
<td>$-3.95%$</td>
<td>$-28.88%$</td>
<td>$-21.74%$</td>
<td>$-21.74%$</td>
</tr>
<tr>
<td>$p_k - 50%$</td>
<td>$-7.67%$</td>
<td>$-30.31%$</td>
<td>$-18.02%$</td>
<td>$-18.02%$</td>
</tr>
</tbody>
</table>

Notes: IRB = incentive rate-based compensation plan, FB = fee-based compensation plan.

### Table 6

| Descriptive statistics of empirical data sets per keyword and campaign. |
|---|---|---|---|---|
| Campaign | Fashion | Mobile phones | Industrial goods | Travel |
| Number of keywords | 306 | 1,233 | 3,035 | 4,204 |
| Profit per conversion | 30,000€ | 100,000€ | 75,000€ | 50,000€ |
| Price per click | Mean | .06€ | .12€ | .26€ | .10€ |
| Rank | Mean | 3.20 | 3.41 | 1.62 | 2.74 |
| Number of consumers searching | Mean | 14,497.14 | 49,442.57 | 1479.24 | 599.07 |
| Clickthrough rate Mean | 7.31% | 3.89% | 6.88% | 14.75% |
| Number of clicks | Mean | 1059.74 | 1923.32 | 101.77 | 88.36 |
| Conversion rate Mean | .90% | .40% | 1.45% | 4.57% |
| Number of conversions | Mean | 68.22 | 234.51 | 26.22 | 8.94 |
| SEM costs per conversion | Mean | 7.15€ | 30.48€ | 17.77€ | 1.82€ |
| Percentage increase in prices per click | Min | 20.00% | 10.00% | 40.00% | 10.00% |
| Max | 160.00% | 150.00% | 180.00% | 160.00% |
| Percentage increase in clickthrough rates | Min | 20.00% | 10.00% | 10.00% | 20.00% |
| Max | 150.00% | 170.00% | 150.00% | 110.00% |

Note: Google averages all variables over a day, so ranks in these data are typically reported to within two decimal points.

on this information. In contrast, with fee-based compensation, the advertiser does not need to reveal its true profit per conversion $p_k$, because it simply sets a fee per conversion that equals the optimal fee for its false profit per conversion.

The deviation of the advertiser’s profit under the fee-based compensation plan from the optimum ($p_k \pm 0\%$) established by the incentive rate-based compensation plan is always equal to $-25.68\%$, a result we know from Table 4. In contrast, the profitability earned through the incentive rate-based compensation plan decreases, as seen in column 2 of Table 5. Column 4 also reveals the effect on variation in profitability across plans. These differences only decrease moderately, from $-25.69\%$ to $-23.85\%$, or $-18.02\%$ if the advertiser reveals a profit per conversion that is 50% higher or lower than actual. Thus, even false information does not change our primary finding: the fee-based compensation plan is substantially worse than the incentive rate-based compensation plan.

### 4.3.2. Results for the empirical data sets

We derive the results for the empirical data sets from the decision problem outlined in Eqs. (1a) and (1b), (3a) and (3b), and (4a)-(4c) for a minimum agency profit of 6,000€ (see Table 7), which best represents the circumstances seen in our real-world data. (For the results for the minimum agency profits of 1,000€ and 3,000€, see Appendix C.) The results for smaller minimum agency profits yield much larger deviations in the advertiser’s and the agency’s profits between the two compensation plans, so the values in Table 7 represent minimum deviations, perhaps even lower than reality.

According to the results in Table 7, the advertiser pays the agency an optimal incentive rate $c^*$ between 22.0% and 31.4% under the incentive rate-based compensation plan. The fees $m^*$ under the fee-based
compensation plan are 11.95€ (39.84% of the advertiser’s profit per conversion) for the fashion campaign and 36.33€, 20.66€, and 8.38€ (36.33%, 27.55%, and 16.76% of the profit per conversion) for the mobile phone, industrial goods, and travel campaigns, respectively. Under the fee-based compensation plan, the advertiser must provide the agency with higher profits (not needed under an incentive rate-based compensation plan) because, otherwise, the agency will bid too low. We recognize this result from the numerical example in Section 3.3 and the simulation study, although the difference between the minimum required profit and the agency’s profit is notable.

The average difference in profit between the two compensation plans across the four campaigns is −29.93%,⁴ varying from −1.14% to −39.23%. These results are generally consistent with the results of the simulation study (average value = −25.69%, range from −6.04% to −40.35%). However, the results of our simulation study do not reflect the fashion campaign accurately, which revealed only small profit differences between the two compensation plans. Therefore, for three campaigns (mobile phones, industrial goods, travel), the deviation in profits is driven by differences both in the agency’s bidding behavior and in the agency’s higher profits. For the fashion campaign, however, the profit deviation is solely a result of differences in the agency’s bidding behavior.

We suggest several reasons for this difference. First, the fashion campaign contains fewer keywords than the other campaigns (306 compared with 1,233–4,204). A smaller campaign typically requires less effort by the agency, because it bids on and monitors fewer keywords. Therefore, a minimum required profit of 6,000€ would be high for a campaign of this size. Second, the profit per conversion

---

Table 7
Results of the empirical data sets for minimum agency profit of 6000€.

<table>
<thead>
<tr>
<th>Campaign</th>
<th>IRB</th>
<th>FB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fashion</td>
<td>13,054.61€ (−1.14%)</td>
<td>12,905.86€</td>
</tr>
<tr>
<td>Mobile phones</td>
<td>238,814.90€ (−39.23%)</td>
<td>145,120.55€</td>
</tr>
<tr>
<td>Industrial goods</td>
<td>65,402.33€ (−26.15%)</td>
<td>48,297.35€</td>
</tr>
<tr>
<td>Travel</td>
<td>266,854.18€ (−23.94%)</td>
<td>202,973.53€</td>
</tr>
<tr>
<td>Fashion</td>
<td>31.40% of profit⁴</td>
<td>11.95€ per conversion</td>
</tr>
<tr>
<td>Mobile phones</td>
<td>2.47% of profit⁴</td>
<td>36.33€ per conversion</td>
</tr>
<tr>
<td>Industrial goods</td>
<td>8.40% of profit⁴</td>
<td>20.66€ per conversion</td>
</tr>
<tr>
<td>Travel</td>
<td>2.20% of profit⁴</td>
<td>8.38€ per conversion</td>
</tr>
<tr>
<td>Fashion</td>
<td>6,000.00€ (0.0%)</td>
<td>6,000.00€</td>
</tr>
<tr>
<td>Mobile phones</td>
<td>6,000.00€ (738.20%)</td>
<td>50,295.32€</td>
</tr>
<tr>
<td>Industrial goods</td>
<td>6,000.00€ (112.55%)</td>
<td>12,752.84€</td>
</tr>
<tr>
<td>Travel</td>
<td>6,000.00€ (412.43%)</td>
<td>30,745.86€</td>
</tr>
<tr>
<td>Fashion</td>
<td>724.89 (−1.35%)</td>
<td>715.10</td>
</tr>
<tr>
<td>Mobile phones</td>
<td>3,525.16 (−34.86%)</td>
<td>2,296.18</td>
</tr>
<tr>
<td>Industrial goods</td>
<td>1,168.83 (−23.93%)</td>
<td>889.12</td>
</tr>
<tr>
<td>Travel</td>
<td>6,336.87 (−23.04%)</td>
<td>4,876.98</td>
</tr>
<tr>
<td>Fashion</td>
<td>SEM costs (−5.38%)</td>
<td>2,547.27€</td>
</tr>
<tr>
<td>Mobile phones</td>
<td>107,701.53€ (−68.24%)</td>
<td>34,201.89€</td>
</tr>
<tr>
<td>Industrial goods</td>
<td>16,259.58€ (−65.35%)</td>
<td>5,631.50€</td>
</tr>
<tr>
<td>Travel</td>
<td>43,989.25€ (−76.97%)</td>
<td>10,129.09€</td>
</tr>
<tr>
<td>Fashion</td>
<td>SEM costs per conversion (−4.08%)</td>
<td>3.56€</td>
</tr>
<tr>
<td>Mobile phones</td>
<td>30.55€ (−51.25%)</td>
<td>14.90€</td>
</tr>
<tr>
<td>Industrial goods</td>
<td>13.91€ (−54.45%)</td>
<td>6.34€</td>
</tr>
<tr>
<td>Travel</td>
<td>6.94€ (−70.08%)</td>
<td>2.08€</td>
</tr>
</tbody>
</table>

Notes: IRB = incentive rate-based compensation plan, FB = fee-based compensation plan.⁴ Profit refers to the overall profit of the advertiser and the agency after SEM costs.

---

⁴ As mentioned in Footnote 3, we could have calculated all percentage differences for each campaign before calculating the average percentage difference. This procedure leads to a deviation of −22.62%.
is smaller for fashion than for the other campaigns (30€ vs. 50€–100€), so a minimum agency profit of 6,006€ would be optimal for the agency regardless of the compensation plan. The fashion campaign with fewer keywords and relatively low profit per conversion, illustrates that both compensation plans perform comparably if the minimum profit for the agency is high in a specific scenario.5

We separate the average difference in the advertiser’s profit (43,707.18€) between the incentive rate-based and fee-based compensation plans in all four campaigns into the part driven by higher agency profit (18,948.51€) and the part driven by bidding behavior differences (24,758.68€ = 43,707.18€ − 18,948.51€). Accordingly, we show that 43.35% of the difference relates to higher agency profit and 56.65% to the difference in bidding behavior.

In summary, we confirm the main findings of our simulation study. The simulation study reveals that the advertiser loses an average of −25.69% in profits under fee-based compensation; in the four empirical data sets, losses amount to −29.93%. We also confirm, as found in the simulation study, that the agency underspends on customer acquisition by an average of 44.76%; in the four empirical data sets, underspending amounts to 4.08–70.08%. This underspending leads to 31.60% fewer acquired customers in the simulation study and to −1.35% to −34.86% fewer acquired customers for the four industries. Finally, we show that the agency receives 66.62% higher profits in the simulation study and in three of the four industries we study empirically (mobile phones, industrial goods, and travel). Recall that in the simulation study, 29.90% of the advertiser’s profit difference stems from overly high profits for the agency, and 70.10% relates to the agency’s restrictive bidding behavior. In the empirical studies, however, 43.35% of the profit difference relates to overly high agency profit, and only 56.65% is caused by the agency’s bidding behavior. The cause of this difference between the simulation study and the empirical data sets is that in 15 of the 30 simulation campaigns (50%), the advertiser already pays the minimum required profit to the agency under the fee-based compensation plan. In real-world industries, however, this minimum payment exists for only one of the four campaigns (25%).

5 In an extreme case, the minimum profit is so high that only the agency realizes profit (and the advertiser no profit). In that case, the advertiser provides the agency with a fee that is equal to its profit per conversion. Consequently, the agency behaves as the advertiser would do and this behavior is equivalent to the behavior under an incentive-rate based compensation plan.

5. Summary, conclusions, and implications

The Internet’s digital environment has made performance-based compensation plans particularly interesting for advertisers because the Internet allows for easy tracking of the number of times ads appear, as well as resulting clicks and conversions. Recently, advertisers have started to pay agencies for their search engine marketing efforts by compensating them with a fee per conversion that must cover both the SEM costs—particularly, the price per click paid to the search engine provider—and the agency’s profit. A nice characteristic of this compensation plan is that it gives the agencies no incentive to overspend on advertising, a major problem with previous commission plans. However, advertisers now face the opposite problem, an unintended incentive for agencies to underspend. Agencies spend less money to generate conversions because they submit lower bids in keyword auctions, resulting in worse ranks, fewer clicks, and therefore fewer conversions for their clients.

Our results indicate that such fee-based compensation plans frequently lead to substantial deviations in the agencies’ bidding behavior; these deviations decrease the advertisers’ profit (by 25.69% in the simulation study and 29.93% in the four empirical studies). Somewhere between 29.90% and 43.35% of these deviations indicate the advertiser’s need to pay the agency a higher fee, so that it earns a profit greater than the minimum required. These higher fees encourage the agency to limit its overspending on advertising, so the additional costs for the advertiser are offset by additional profits for the agency. Moreover, we find that the decrease in advertisers’ profit remains the same size regardless of whether the advertiser is uncertain about its profit per conversion. Profit only slightly decreases if the advertiser does not truthfully reveal this profit per conversion.

Previous studies have shown that incentive-compatible compensation plans better align the interests of the principal (the advertiser) and the agent (the agency) and thereby increase profits (see Coughlan & Sen, 1989). We proceed to outline the magnitude of the profit differences. The remarkable and robust differences we find between fee- and incentive rate-based compensation plans (−25.69% and −29.93%) indicate that a poor compensation plan, based on a fee per conversion, seriously harms profit. These numbers should strongly encourage companies to consider implementing more incentive-aligned compensation plans.

Yet fee-based compensation plans remain widespread, largely because search engine providers offer tracking technologies that report the agency’s spending and the resulting clicks and conversions. A natural next step would be to use such compensation plans in other areas of online marketing, such as display advertising or affiliate marketing. Our results indicate that such extensions should be treated with caution, because agencies have strong incentives to underspend on advertising, with serious implications for the advertiser’s profitability. We freely acknowledge that many firms have used compensation plans that provide incentives to spend too much money on advertising, but we believe there is serious danger of moving in the opposite direction.

Certainly our findings are not without limitations. We approximate prices per click by bids, an approach that is common in relevant literature and seems sensible, considering the empirical evidence. The compensation negotiation process between advertisers and agencies is interesting but is beyond the scope of our research. Also, we do not include dynamic effects over time, because we consider only one advertiser in each industry (Yao & Mela, 2011). If some or all advertisers switch to an incentive rate-based compensation plan, their agencies would submit higher bids and generate higher SEM costs for all agencies. Thus, it might be interesting for further research to determine the point at which an additional advertiser can no longer benefit from switching to the incentive rate-based plan. Furthermore, advertisers might enjoy the fee-based compensation plan because it reduces uncertainty in the costs per conversion, which can make advertising budgeting easier. Additional research could explore such advantages, which we do not consider in our analysis.

Additionally, we do not address how risk aversion affects profit differences. In sales force management literature, the principal is usually risk neutral and the agent is risk averse. The agent is a single entity with an interest in a stable, rather than volatile, income (see Albers, 1996; Basu, Lal, Srinivasan, & Staelin, 1985; Coughlan, 1993; Coughlan & Sen, 1989). In search engine marketing though, the agent is usually a firm (i.e., agency) and not a single person, so risk aversion may be less likely. If the agency were risk averse and uncertainty existed, the agency would bid less aggressively and submit lower bids to avoid losses resulting from overbidding. Although the agency shares profits and losses (i.e., the cost of placing ads with the search engine) with the advertiser under the incentive rate-based compensation plan, it must cover all advertising costs under the fee-based compensation plan. Therefore, the risk premium that the advertiser pays under uncertainty should be higher under the fee-based plan, and the profit differences between the plans could increase further if the agency is risk averse. Yet, risk aversion also makes two-part contracts more attractive, including contracts in which the agency receives a fixed (non-performance-based) payment and a variable (performance-based) payment. With these contracts, the advertiser avoids the risk premium for the fixed payment (see Albers & Mantrala, 2008; Basu et al., 2009).
et al., 1985; Coughlan & Sen, 1989), even though cross-sectional empirical studies do not support this conclusion (Krafft, Lal, & Albers, 2004). Certainly, a precise analysis of the effects requires that uncertainty is captured in the analytical model, which we do not accommodate. Still, our results likely indicate that performance-based payment should be based on the advertiser’s realized profit. The behavior of the agency might deviate even further from the advertiser’s preferred optimal behavior if the fee decreases, because the agency receives only a fixed payment. Alternatively, the advertiser could bear all SEM costs and pay the agency a commission linked to the number of conversions. Such compensation plans still give the agency an incentive to overspend on advertising, though. We therefore recommend further research to elaborate in more detail the influence of risk aversion and uncertainty on the optimal compensation plan, as well as to elaborate the optimality of other compensation plans, such as two-part contracts.

Finally, our analysis assumes that agencies are myopic and maximize the single-period profit, although the agency might realize that a satisfied advertiser is more likely to renew a contract. Future research should further analyze our results in a multi-period setting.

Acknowledgments

The authors thank Oliver Hinz, Martin Natter, Jochen Reiner and Thomas Otter as well as seminar participants at the University of New South Wales and London Business School for their valuable comments on earlier drafts of the article. They also gratefully acknowledge financial support from the E-Finance Lab at the House of Finance at Goethe-University Frankfurt.

Appendix A. Analysis of maximum differences between bids and prices paid

To verify the appropriateness of the approximation of the price per click by the advertiser’s bid (a frequent approximation; see Ghose & Yang, 2009; Yang & Ghose, 2010), we empirically compare their differences. We analyze data from the search engine provider Yahoo according to 364 popular keywords from 14 different industries, at up to three different points in time (March 2006, June 2006, February 2007). These data contain the prices for each keyword at every single rank as a result of the first-price auction conducted by Yahoo at that point in time. The maximum deviations between paid prices and bids of a second-price auction (as performed by Yahoo and Google) can be derived by comparing the price at rank $x$ (resulting from bids at prices between rank $x$ and rank $x+1$) with the price at rank $x+1$. For a new bidder, these differences should be approximately 50% lower, because, on average, the bid of a new bidder is likely to fall in the middle between the price at rank $x$ and $x+1$.

Table A1 shows that the average maximum difference across all industries and all keywords is 0.0547€; the median is 0.0373€, so some outliers shift the mean upward. If we consider that the difference for a new bidder is 50% lower, the differences diminish to 0.0262€ (median = 0.0183€). Thus, the difference is in the range of 1–2 cents, and our approximation seems feasible, in line with the assumptions of Ghose and Yang (2009) and Yang and Ghose (2010).

Appendix B. Percentage increases in prices per click and clickthrough rates

We collect data from Google’s traffic estimator (https://adwords.google.com/select/TrafficEstimatorSandbox) to derive the ranges for the percentage increases in prices per click and clickthrough rates and randomly draw from these ranges in both the simulation and the empirical studies. The traffic estimator reports the potential number of searches for a given keyword, as well as the estimated price per click and the estimated number of clicks for an average advertiser at a given rank. Using the traffic estimator, we collected data on 30 keywords in each of the four industries (fashion, mobile

Table A1

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean over all industries</td>
<td>N = 5,973</td>
<td>N = 1,191</td>
<td>N = 3,309</td>
</tr>
<tr>
<td>Beauty</td>
<td>N = 0</td>
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<td>N = 202</td>
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<td>Cars</td>
<td>N = 0</td>
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<td>Computing</td>
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<td>N = 453</td>
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<tr>
<td>Dating</td>
<td>N = 0</td>
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<td>N = 243</td>
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<tr>
<td>Electronics</td>
<td>N = 0</td>
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<td>N = 393</td>
</tr>
<tr>
<td>Fashion</td>
<td>N = 0</td>
<td>.</td>
<td>N = 240</td>
</tr>
<tr>
<td>Financial Services &amp; Insurances</td>
<td>N = 1,572</td>
<td>N = 299</td>
<td>N = 376</td>
</tr>
<tr>
<td>Food &amp; Beverages</td>
<td>N = 0</td>
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<td>N = 199</td>
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<td>Real Estate</td>
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<tr>
<td>Services</td>
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<td>N = 237</td>
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<tr>
<td>Shopping</td>
<td>N = 0</td>
<td>.</td>
<td>N = 0</td>
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<td>Telecommunications</td>
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<td>N = 187</td>
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<tr>
<td>Travel</td>
<td>N = 2,401</td>
<td>N = 153</td>
<td>N = 407</td>
</tr>
<tr>
<td>Wellness</td>
<td>N = 0</td>
<td>.</td>
<td>N = 0</td>
</tr>
</tbody>
</table>
phones, industrial goods, and travel) at three different ranks (usually between 1 and 3, 3 and 5, and 5 and 8), which creates 90 observations per industry (30 keywords times 3 ranks). To derive the percentage increases in prices per click and clickthrough rates, we then estimate a keyword-level, log-linear regression of the logarithm of clickthrough rates on the rank. Table B1 reports the results for the percentage increases in prices per click and clickthrough rates for fashion, mobile phones, industrial goods, and travel.

In the simulation study, we use the minimum of all percentage increases across industries to define the lower bound of the range and the maximum to define the upper bound. We round the minimum percentage increase down to the nearest ten (floor function) and round the maximum percentage increase up to the nearest ten (ceiling function). The percentage increases in prices per click vary between 10% and 180%, and the percentage increases in clickthrough rates range between 10% and 170%. The middle value divides the range into two groups.

In our empirical study, we only use industry-specific results to define ranges for the percentage increases in prices per click and clickthrough rates for each industry. As we note in the main text, the percentage increases in prices per click vary between 20% and 160% for the fashion industry, 10% and 150% for mobile phones, 40% and 180% for industrial goods, and 10% and 160% for the travel industry. The percentage increases in clickthrough rates vary between 20% and 150% for the fashion industry, 10% and 170% for mobile phones, 10% and 150% for industrial goods, and 20% and 110% for the travel industry.

Appendix C. Additional results from the empirical data sets

Table C1 (continued)

<table>
<thead>
<tr>
<th>Industry</th>
<th>IRB</th>
<th>FB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum agency profit</td>
<td>1,000€</td>
<td>3,000€</td>
</tr>
<tr>
<td></td>
<td>1,000€</td>
<td>3,000€</td>
</tr>
<tr>
<td>Industrial goods</td>
<td>1,000.00€</td>
<td>1,000.00€</td>
</tr>
<tr>
<td></td>
<td>1,000.00€</td>
<td>1,000.00€</td>
</tr>
<tr>
<td>Fashion</td>
<td>234,814.90€</td>
<td>234,814.90€</td>
</tr>
<tr>
<td></td>
<td>145,120.55€</td>
<td>145,120.55€</td>
</tr>
<tr>
<td></td>
<td>70,402.33€</td>
<td>70,402.33€</td>
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<tr>
<td></td>
<td>271,854.18€</td>
<td>271,854.18€</td>
</tr>
<tr>
<td></td>
<td>30,745.86€</td>
<td>30,745.86€</td>
</tr>
<tr>
<td></td>
<td>54.45%</td>
<td>54.45%</td>
</tr>
<tr>
<td></td>
<td>34,201.89€</td>
<td>34,201.89€</td>
</tr>
<tr>
<td></td>
<td>76.97%</td>
<td>76.97%</td>
</tr>
<tr>
<td></td>
<td>23.93%</td>
<td>23.93%</td>
</tr>
<tr>
<td></td>
<td>70.08%</td>
<td>70.08%</td>
</tr>
<tr>
<td></td>
<td>51.85%</td>
<td>51.85%</td>
</tr>
</tbody>
</table>


*Optimal compensation for incentive rate–based compensation in percentage of overall profit (profit of the advertiser and the agency after SEM costs) and for fee–based compensation in Euros per conversion.

References


Dynamics in the international market segmentation of new product growth

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A B S T R A C T

Prior international segmentation studies have been static in that they have identified segments that remain stable over time. This paper shows that country segments in new product growth are intrinsically dynamic. We propose a semiparametric hidden Markov model to dynamically segment countries based on the observed penetration pattern of new product categories. This methodology allows countries to switch between segments over the life cycle of the new product, with time-varying transition probabilities. Our approach is based on penalized splines and can thus be flexibly applied to any nonstationary phenomenon, beyond the new product growth context. For the penetration of six new product categories in 79 countries, we recover the dynamic membership of each country to segments over the life cycle. Our findings reveal substantial dynamics in international market segmentation, especially at the beginning of the product life. Finally, we exploit the dynamic segments to predict the national penetration patterns of a new product before its launch and show that our forecasts outperform forecasts derived from alternate parametric and/or static methods. Our results should encourage multinational corporations to adopt dynamic segmentation methods rather than static methods.

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1. Introduction

Country segmentation is fundamental to any successful international marketing strategy (Steenkamp & Ter Hofstede, 2002). The globalization of firms and markets enhances the need for the cross-border exchange of experiences and market research that accounts for both similarities and differences across markets. With globalization comes an increased understanding of the similarities and differences between markets.

Various segmentation bases have been suggested for international markets; particularly relevant to the present paper is the segmentation of countries based on the sales, adoption or penetration patterns of new products over the life cycle (see, e.g., Geelens & Steenkamp, 2007; Helsen, Jedidi, & DeSarbo, 1993; Kumar, Ganesh, & Echambadi, 1998; Sood, James, & Tellis, 2009). Such segmentation is often used to select the sequence of countries to enter (Tellis, Stremersch, & Yin, 2003). Grouping countries based on the penetration patterns that new products show over time is especially relevant if one considers both the high financial stakes involved in introducing a new product globally and the substantial differences that new product growth patterns show across countries and country segments (Dekimpe, Parker, & Sarvary, 2000; Desiraju, Nair, & Chintagunta, 2004; Gatignon, Eliashberg, & Robertson, 1989; Mahajan & Muller, 1994; Stremersch & Lemmens, 2009; Stremersch & Tellis, 2004; Van den Bulte & Stremersch, 2004; Van Everdingen, Fok, & Stremersch, 2009). The idea of such segmentation is that the penetration patterns of new products are likely to show similarities across countries when these countries face similar demand-side (e.g., national culture) and supply-side factors (e.g., regulation), as demonstrated by Stremersch and Lemmens (2009).

Prior research has cited multiple reasons why country segmentation on the basis of penetration patterns is relevant to companies. First, it enables cross-fertilization and experience sharing between managers of the same segment in different countries (Bjømøl, Paas, & Vermunt, 2004). Second, the sales evolution of a new product in one country can be used as reference point by managers in another country that belongs to the same segment (Steenkamp & Ter Hofstede, 2002). Third, international segmentation can improve forecasting accuracy regarding the growth of new products, especially prior to launch, which is similar in principle to analogical diffusion models (Bass, 2004; Ofek, 2005). A firm may also select a test country within a segment to explore the sales potential not only for that test market but also, by analogy, for the entire segment (Green, Frank, & Robinson, 1967). Firms can exploit the benefits of country segmentation both at the individual brand and at the product category level (e.g., brand diffusion versus category diffusion models or brand management versus category management).
A key shortcoming of the country segmentation methods in the marketing literature is their static nature (Steenkamp & Ter Hofstede, 2002). An implicit assumption is made that the segments are stationary in both structure (segment composition or membership) and characteristics (segment profiles). In this model, the membership of a country to a segment does not vary over the product life cycle. For instance, Helsen et al. (1993) segment countries based on the time-invariant parameters of the Bass (1969) diffusion model in a mixture regression framework. Similarly, Jedidi, Krider, and Weinberg (1998) cluster movies according to their share-of-revenue patterns over time. Recently, Sood et al. (2009) propose a semiparametric model where they estimate diffusion curves, which they subsequently cluster using functional principal components (Ramsay & Silverman, 2005).

However, the nonstationary nature of new product adoption endangers the temporal stability of international segments, which are likely to show dynamics (Wedel & Kamakura, 2000). The combined studies of Tellis et al. (2003) and Stremersch and Tellis (2004) provide indirect evidence for the relevance of this time dependence. Using the same European diffusion data, they find that the factors that drive early growth (i.e., time-to-takeoff) are different from the factors that drive late growth (i.e., time-to-slowdown). Moreover, Golder and Tellis (2004) and Stremersch and Lemmens (2009) show that the influence of variables that affect new product growth varies over time.

In this paper, we demonstrate that country segmentation based on the penetration pattern of new product categories is not static but inherently dynamic. To accommodate dynamics, we develop a semiparametric hidden Markov model (HMM) that allows country segment membership to vary flexibly over time. The paper extends recent advances in time-varying household segmentation (e.g., Du & Kamakura, 2006; Paas, Vermunt, Bijmolt, & Journal of the Royal Statistical Society, 2007), dynamic customer value segmentation (Brangule-Vlagsma, Pieters, & Wedel, 2002; Homburg, Steiner, & Totzek, 2009) and customer relationship dynamics (Netzer, Lattin, & Srinivasan, 2008) to an international scope and combines them with recent advances in semi-parametric modeling of new product growth patterns with penalized splines (Stremersch & Lemmens, 2009).

We apply our semiparametric dynamic segmentation method to country-level penetration data from six product categories of Information and Communication Technology (ICT) products and media devices across 79 developed and developing countries between 1977 and 2009. For this specific set of product categories, we identify three latent country segments that show substantial dynamics in membership probabilities and size over time, especially at the beginning of the product life cycle. Dynamic segments provide a better fit than static segments or segments based on geographic area (e.g., North America and Western Europe). In addition, a semiparametric response function offers a better fit than a parametric specification. Our dynamic segmentation model also shows outstanding prelaunch forecasting performance, in most cases outperforming static and/or parametric segmentation methods. While we apply the model to product categories, it is also possible to apply it to brands because unlike (parametric) diffusion models such as the Bass diffusion model, our semiparametric approach does not impose a (behavioral) structure.

This paper has important implications for firms and international public policy bodies that use country segmentation methods. Many of these entities use an exogenously defined regional segmentation criterion (see e.g., Ghauri & Cateora, 2006, p. 492) or, if they are more sophisticated, a static model-based segmentation method. We show that both are inaccurate because segments are intrinsically dynamic. Therefore, both approaches may lead to inappropriate decision making and imprecise forecasts as compared with dynamic segments. We suggest that analysts change their current practice (i.e., static segmentation) and derive, for their respective industries and product categories, a dynamic segmentation of the countries in which they compete.

The remainder of the paper is organized as follows: the second section presents a short overview of the recent developments in international segmentation modeling, the third section describes the methodological framework used to dynamically segment countries over time, the fourth section includes the data description and presents the empirical findings, and the final section presents managerial implications and conclusions.

2. Existing international segmentation methods

Most research has used established segmentation algorithms developed in the statistical literature, such as finite-mixture models (Helsen et al., 1993; Ter Hofstede, Steenkamp, & Wedel, 1999) or variations of k-means clustering (Chaturvedi, Carroll, Green, & Rotondo, 1997; Homburg, Jensen, & Krohmer, 2008; Kale, 1995). Few international segmentation studies have focused on the development of new methodological frameworks. Recently, scholars have proposed several new methods for studying international segmentation. In particular, hierarchical Bayesian models with segment-specific response parameters (Ter Hofstede, Wedel, & Steenkamp, 2002) allow spatial dependence within and between segments. The multilevel finite-mixture model proposed by Bijnont et al. (2004) accounts for different levels of aggregation (e.g., consumer and country levels).

Other interesting ongoing methodological developments are functional data analysis and functional clustering, as in Sood et al. (2009) for product-country segmentation (or Foutz and Jank, 2010, for product segmentation). The main benefit of such approaches, beyond the flexibility that functional analysis offers as a nonparametric framework, is that the econometrician can cluster the growth curves of new products globally based on their functional shape. Any possible shape can be managed.

Time dependence remains an important concern in international segmentation. As discussed by Steenkamp and Ter Hofstede, “over time, the number of segments, segment sizes and structural properties of international segments may change. […] This issue has not received rigorous attention yet.” (Steenkamp & Ter Hofstede, 2002, p. 209). From a managerial viewpoint, ignoring dynamics in international segments is likely to lead to suboptimal marketing strategies. From an estimation viewpoint, the violation of the assumption of stationarity may invalidate model estimation when the phenomenon under study is by nature nonstationary or when the data range spans a long time period, such as in diffusion studies. Recent methodological advances in segment dynamics modeling are (hidden) Markov models (Brangule-Vlagsma et al., 2002; Du & Kamakura, 2006; Homburg et al., 2009; Letchty, Pieters, & Wedel, 2003; Montgomery, Li, Srinivasan, & Letchty, 2004; Netzer et al., 2008; Paas et al., 2007; Ramaswamy, 1997). Applied to a collection of time series data, an HMM can identify, for each time period, the segment to which a realization belongs. HMMs allow segment membership to dynamically vary over time. Existing marketing applications have focused on customer or household segmentation and have modeled the finite-mixture response function in a parametric way. Our research extends the use of the HMM to international country segmentation and proposes the use of a semiparametric framework where time series data are not restricted to a specific functional form.

3. A semiparametric hidden Markov model for dynamic country segmentation

This section first describes the semiparametric hidden Markov model that we propose to dynamically segment countries. Then, we explain how we use this approach to make new product growth forecasts, and we present several alternative benchmark models.

3.1. A new dynamic segmentation framework

For every country i, with i = 1,...,n and product category j, with j = 1,...,J we observe a penetration pattern yij1,yij2,...,yijTij, where Tij is the number of sample points available for this product-country
combination. In our application, we define penetration in percentage as the number of devices or subscriptions used by a population divided by the number of users (see the data section). Prior to launch, we have \( y_{it} = 0 \) up to \( t = 0 \). Note that we consider duration time rather than calendar time because the goal of the analysis is to pool the penetration data of multiple product categories launched at different calendar times and to extract regularities or commonalities in diffusion patterns across countries. We let \( y_{it} = (y_{it}, \ldots, y_{it}, \ldots, y_{it}) \) be the vector containing the penetration data in country \( i \) at time \( t \) of all product categories under consideration. As the number of observed sample points could differ per product category, the number of components in the vector \( y_{it} \) is allowed to vary over time. We denote \( T_i = \max_t T_i \) and write, for notational convenience, for every country \( T_i = T \).

We model the penetration of product \( j \) in country \( i \) at time \( t \) using a semiparametric hidden Markov model. A hidden Markov model is a probabilistic model of the joint probability of a collection of random variables, here \( (y_{it}, \ldots, y_{it}) \). The distribution of \( y_{it} \) depends on the value taken by a hidden (or latent) state variable in the set \( \{1, \ldots, S\} \) of possible states, with \( S \) being the total number of hidden states. We denote \( (i, t) \), the value of the hidden state variable for country \( i \) at time \( t \). Countries that share the same value \( s(i, t) \) belong to the same latent segment at time \( t \). To allow for time-varying country membership to the latent segments, each country \( i \) follows a particular (hidden) sequence of states \( s(i, 1), \ldots, s(i, T) \), the state path. Using the time-varying segmentation basis \( y_{it} \), we model the estimate and obtain the probability of each country belonging to each latent segment at any given time point during the product life cycle.

#### 3.1.1. Hidden Markov Model

The model is composed of two parts: (i) a response component that connects the state variable to the observed responses at any given time point and (ii) a structural component that models changes in latent segments across time periods.

We model the penetration of product \( j \) in country \( i \) at time \( t \), given that country \( i \) belongs to latent segment \( s(i, t) \) as

\[
y_{ijt} = f_{s(i, t)} + g_{s(i, t)} + \epsilon_{ijt}, \quad \epsilon_{ijt} - N(0, \sigma^{2}_{ijt}). \tag{1}
\]

For every segment \( s \), with \( 1 \leq s \leq S \), we denote that \( f_{s} \) is a segment-specific function, and \( g_{s} \) as the corresponding segment-specific deviation from the segment function. Product-specific deviations vary between segments and capture the heterogeneity between products. These functions can be modeled in a parametric or semiparametric fashion. To keep our segmentation method as flexible as possible, we opt for a penalized spline semiparametric specification for both \( f_{s} \) and \( g_{s} \), as detailed in the next subsection. Another option would have been to specify \( f_{s} \) and \( g_{s} \) as parametric functions of the time \( t \) (e.g., Bass, 1969). We compare both possibilities in the empirical analysis. Furthermore, we allow the error term in \( (1) \) to be heteroscedastic with \( \sigma^{2}_{ijt} = \sigma^{2}_{it} \) and each \( \epsilon_{ijt} \) to follow a first-order autoregressive process with a common autoregressive parameter. This specification accounts for penetration curves being cumulative time series and provides a better fit to the data than a model with homoscedastic errors and/or without autocorrelation. For a fixed time point, Eq. \( (1) \) can be interpreted as a finite-mixture model, defining a country segmentation based on the observed penetration values across product categories at that time period. Fig. 1 proposes a graphical representation of our semiparametric HMM in the case of three states or segments.

The structural component follows a first-order Markov chain. In particular, it assumes that membership to the latent segment at time \( t \) is affected only by segment membership at \( t - 1 \), but not by latent segment membership at earlier periods. The initial latent segment probability \( \pi_s = P(s(i, 1) = s) \) is the probability of belonging to segment \( s \) at \( t = 1 \) while the time-varying transition probability \( \pi_{st, t+1} = P(s(i, t + 1) = s_t | s(i, t) = s) \) denotes the probability of switching from segment \( s_t \) at \( t \) to segment \( s_{t+1} \) at \( t + 1 \), for \( t = 1, \ldots, T - 1 \). The above probabilities are the same for all countries and are referred to as the prior probabilities. The prior probability that a country follows the path \( s_1, \ldots, s_T \) is then given by \( \pi_{s_1} \pi_{s_1, s_2} \cdots \pi_{s_{T-1}, s_T} \) for any \( s_1, \ldots, s_T \) using the first-order Markov property.

In our approach, the transition probabilities are time-varying (or time-heterogeneous). In the nonstationary new product growth context, one can easily conceive that transition probabilities in the period immediately following the launch of a new product are likely to differ from transition probabilities after the product has matured. For instance, the first years after launch tend to show higher variability in state membership (lower stickiness of the states) than later years when the total market potential is almost reached. We allow these transition probabilities to vary freely over time. One can possibly extend this formulation by letting the probabilities depend on available (time-varying) covariates, as proposed by Paas et al. (2007).

To identify the labels of segments, we use the restriction \( f_{s_1} - f_{s_2} \leq \cdots \leq f_{s_T} \) at each time point, allowing us to identify the segment with the largest value of the index \( s \) as the segment with the highest penetration level. A similar identification restriction was made in Netzer et al. (2008). Note that this restriction does not prevent a country from moving from the high- to the low-penetration segment (or vice versa), which would result in crossing penetration patterns.

Combining the semiparametric response model given by Eq. \( (1) \) and the first-order Markov model yields a semiparametric hidden Markov model. The total likelihood function is given by

\[
\prod_{i=1}^{T} \sum_{s=1}^{S} \sum_{s_1=1}^{S} \sum_{s_2=1}^{S} \ldots \sum_{s_{T-1}=1}^{S} \pi_{s_1} \pi_{s_1, s_2} \cdots \pi_{s_{T-1}, s_T} L_i(y_{it}|s(i, 1), \ldots, s(i, T)),
\]

with \( L_i(y_{it}|s(i, 1), \ldots, s(i, T)) \) being the conditional likelihood of the series for country \( i \) given the state path. This conditional likelihood is easy to compute. For instance, in the absence of serial correlation in the error terms in Eq. \( (1) \), we have \( L_i(y_{it}|s(i, 1), \ldots, s(i, T)) = \prod_{t=1}^{T} L_i(y_{it}|s(i, t)) \), where \( L_i(y_{it}|s(i, t)) \) is the likelihood of a normal distribution with mean \( \mu_{s(i,t)} = (\mu_{s_1}, \ldots, \mu_{s_T}) \) and covariance matrix \( R_i \). Here, \( \mu_{s(i,t)} = f_{s(i,t)} + g_{s(i,t)} \) is the expected penetration level of product \( j \) in segment \( s \) at time \( t \), and the matrix \( R_i \) is the covariance matrix of the error terms \( \epsilon_{ijt} \), \( 1 \leq t \leq T \).

If we allow for autocorrelation in the error terms, the expression for the likelihood becomes slightly more complex because the distribution of \( y_{it} \) depends on not only the state to which it belongs anymore but also \( y_{it-1} \) and the previous state.

#### 3.1.2. Semiparametric Modeling Using Penalized Splines

To ensure full flexibility in the choice of the time-varying segmentation basis, we model the segment-specific function and the product-specific deviations in a semiparametric fashion, using penalized or p-splines. Previous diffusion research has argued that parametric diffusion models suffer from several limitations that semiparametric modeling can address. For instance, parameters tend to be biased when the observed time window is too short (Bemmanor & Lee, 2002; Van den Bulte & Lilien, 1997) or when data contain repeat purchases (Hardie, Fader, & Wisniewski, 1998; Van den Bulte & Stremersch, 2004). Penalized splines constitute a highly flexible and modular approach to model how a response variable is affected by covariates, in this case by duration time (Ruppert, Wand, & Carroll, 2003). Splines have become increasingly popular in medicine (e.g., Durban, Hazekal, Wand, & Carroll, 2005), finance (e.g., Jarrow, Ruppert, & Yu, 2004), and, recently, in marketing (Kalyanam & Shively, 1998; Sioot, Fok, & Verhoef, 2006; Stremersch & Lemmens, 2009; Van Heerde, Leeflang, & Wittink, 2001; Wedel & Leeflang, 1998).

We can construct a spline as a linear combination of \( K \) linear bases, which are broken lines \( \{t - \kappa_j\} \), truncated at knot \( \kappa_j \) with \( 0 \leq \kappa_j \leq T \).
for \( k = 1, \ldots, K \) (i.e., the knot is the location where the broken lines are tied together).\(^2\) If we combine such bases with different knots ranging from 0 to \( T \) and assign weights \( u_{t-1}, u_{t K} \) to each, we can fit any nonlinear, smoothed curve \( h(t) = \sum_{k=1}^{K} u_{t-1} u_{t K} (t-\kappa_k) \). To ensure the smoothness of the curve, these weights are penalized (i.e., they are subject to the constraint \( \sum u_{t-1} u_{t K} < U \), for some constant \( U \)) (see Ruppert et al., 2003, pp. 65–67, for more details). This weighting mechanism explains why splines are called penalized splines. The number of knots, \( K \), must be large enough to ensure the flexibility of the curve. The level of smoothing of the penalized splines is controlled by the variance of \( u_k \) (i.e., \( \sigma^2_k \)). A large variance corresponds to a wiggly function while a small \( \sigma^2_k \) yields a smooth function. Note that the variance is estimated using the maximum likelihood (Wand, 2003).

The segment-specific function (see Eq. (1)) is written as a penalized spline

\[
f_{st} = \beta_s t + \sum_{k=1}^{K} u_{sk} (t-\kappa_k),
\]

with fixed slope parameters \( \beta_s \) and random coefficients \( u_{sk} \sim N(0, \sigma^2_k) \). It can be interpreted as an expected penalization pattern observed in the country segment \( s \). This component reflects the regularities in the penetration patterns that new products exhibit in this specific country segment. In turn, deviations for product \( j \) from the segment-specific function are modeled similarly as

\[
g_{sjt} = \alpha_{sj} t + \sum_{k=1}^{K} v_{skj} (t-\kappa_k),
\]

with the random parameters \( \alpha_{sj} \sim N(0, \sigma^2_{sj}) \) and \( v_{skj} \sim N(0, \sigma^2_{skj}) \).

The above formulation treats products as being nested into segments and therefore accounts for product-segment interaction effects. It allows the product-specific deviations to vary across country segments. Controlling for the product deviations allows us to define an international segmentation solution that is generalizable to the set of product categories considered, making an abstraction of the product-specific peculiarities and the noninformative variation in the data (e.g., measurement error). Note that the resulting country segments may be different if one considers a different pool of product categories (e.g., high tech products versus kitchen and laundry appliances). For firms, the best approach would be to consider their product divisions and pool across all the products of each respective division.

### 3.1.3. Parameter estimation

The model parameters are estimated using a maximum likelihood and computed using the Expectation-Maximization (EM) algorithm. We refer to Zucchini and MacDonald (2009) for details on the EM algorithm applied to the hidden Markov model.\(^3\) The outline follows: denote \( \Theta \) as the vector collecting all unknown parameters of the model, including the initial state probabilities, the transition probabilities, and the unknown \( f_{st} \) and \( g_{sjt} \); and assume that, at the \( k \)th step of the algorithm, an estimate \( \Theta_k \) is available. In addition, \( P_{kj} \) and \( q_{kj} \) are the probability and the likelihood, assuming that \( \theta = \Theta_k \). In the E-step, we compute the following: (i) the posterior segment membership probabilities, \( P_{k}(s(i, t) = s | y_{i1}, \ldots, y_{iT}) \), (i.e., the probability of belonging to segment \( s \) at time \( t \) for country \( i \), conditional on the observed time series) and (ii) the posterior segment transition probabilities. These posterior probabilities can be computed efficiently using the Baum–Welch forward-backward algorithm (Baum, Petrie, Soules, & Weiss, 1970, see also Paas et al., 2007). By averaging the posterior probabilities \( P_{k}(s(i, t) = s | y_{i1}, \ldots, y_{iT}) \) over all the countries, we obtain an update of the estimates of the initial state probabilities \( \pi_s \) for \( s = 1, \ldots, S \). Similarly, by averaging the posterior segment transition probabilities over all countries, we obtain an update of the transition probabilities \( P_{kj}^{\pi_{k+1}} \). In the M-step, we maximize the expected log-likelihood, leading us to maximize

\[
\sum_{i=1}^{n} \sum_{t=1}^{T} \log P_k(s(i, t) = s_1, \ldots, s(t, T) = s_T | y_{i1}, \ldots, y_{iT}) L_k(y_{i1}, \ldots, y_{iT}, s_1, \ldots, s_T)
\]

with respect to the unknown parameters \( f_{st} \) and \( g_{sjt} \) appearing in the likelihood, yielding a new estimate \( \Theta_{k+1} \). Maximizing the expected log-likelihood corresponds to computing a weighted maximum likelihood estimator. Alternatively, the observations could have been randomly assigned to the latent states according to the posterior probabilities of the state paths. The standard estimators are then computed from the data allocated to the different states. This approach is called the Stochastic Expectation-Maximization (SEM) algorithm and was first proposed by Celeux and Govaert (1991). We then iterate the E and M steps until we reach convergence of the model fit criteria. We start the algorithm with equal posterior latent segment membership probabilities \( 1/S \), and equal latent posterior transition probabilities \( 1/S \), for \( t = 1, \ldots, T - 1 \).

Note that our model-based segmentation provides richer information than “hard” clustering algorithms (e.g., \( K \)-means), as it yields the probabilities of each country belonging to each of the various segments at every time point.

\(^2\) The notation \( h(x) = (x)_+ \) indicates that the function \( h \) equals zero when \( x < 0 \) and equals \( x \) for \( x \geq 0 \).

\(^3\) Most textbooks only present the homogenous version of the HMM, where the transition probabilities are not time-dependent. We carefully adapted all formulas – in particular of the Baum–Welch algorithm – to the nonhomogeneous case. For brevity, we only report here the most important ingredients of the EM algorithm. Full details are available from the first author upon request.
3.1.4. Model fit criteria and the optimal number of segments

As is commonly done in segmentation analysis (see e.g., Wedel & Kamakura, 2000), we evaluate the fit of the model by computing the Bayesian Information Criterion (BIC) based both on the estimated likelihood given in Eq. (2) and on the total number of free parameters in the model (Greene, 2003, p. 160). The latter includes the transition probabilities and starting probabilities and the parameters in the specification of both the segment curve (Eq. 3) and the product-deviation curve (Eq. 4). In the context of our semiparametric mixed-effect model, we compute the number of free parameters following the approach proposed by Vaida and Blanchard (2005, see also Ruppert et al., 2003), yielding a number ranging between the sum of the number of fixed effects and variance components and the sum of the number of fixed and random effects.

In addition to the Bayesian information criterion, we also evaluate the separability of the segments and the stability of the segmentation to changes in the data (i.e., its robustness). The normalized entropy criterion (NEC) can be computed to investigate the degree of separation in the posterior probabilities (Grover & Vriens, 2006, pp. 402–403, 416). A lower NEC indicates that the segments are separated well from one another. In addition, a value less than one indicates that the identified segmentation structure does exist (Biemacki, Celeux, & Govaert, 1999).

To study the stability of the segmentation to changes in the data, we apply the model explorer algorithm of Ben-Hur, Elisseeff, and Guyon (2002), which makes use of the following cross-validation. We randomly separate 10% of the countries and apply the model to the remaining 90%. Repeating this operation 10 times, we obtain 10 different segmentations, separate 10% of the countries and apply the model to the remaining 90%.

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Adjusted Rand Index (ARI) generalized to probabilistic segmentation in which pairwise similarity indices are computed using the popular Repeating this operation 10 times, we obtain 10 different segmentations, separate 10% of the countries and apply the model to the remaining 90%.

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(ii) whether forecasts are made before a new product (category) is initially launched (i.e., is not available in any country yet) or whether forecasts are made before a new product (category) is initially launched in a given country (local launch) but has already been launched in other countries.

3.2. Forecasting procedure

Country segmentation can be a powerful instrument for prelaunch forecasts. Prior to the first launch of a product, firms do not observe any product-specific information on the actual adoption of the new product or product category. In such cases, firms can rely on test market data, consumer surveys or “clinics” (Blattberg & Golany, 1978; Urban, Hauser, & Roberts, 1990), advance purchase orders (Moe & Fader, 2002), and/or the available sales or adoption history of similar products introduced in the past using analogical diffusion models (Lee, Boatwright, & Kamakura, 2003; Ofek, 2005). For international markets, firms can also pool the information on similar products across multiple countries, rather than using the information for a single country (Talukdar, Sudhir, & Ainslie, 2002). In this context, country segments should indicate the relevant set of countries to be considered in prelaunch forecasting. If the premise that we stated above is correct (i.e., that information contained in dynamic segments of countries is richer than information contained either in static segments of countries or in single countries), then the dynamic segmentation method should outperform alternative methods based on static segments of countries or past patterns in single countries. This idea is similar to the spatial model proposed by Bronnenberg and Sismeiro (2002) that infers data in markets where little or no data are available using information available from other geographic locations.

The use of segments to make prelaunch forecasts depends on the following: (i) whether forecasts are made before a new product (category) is initially launched (i.e., is not available in any country yet) or (ii) whether forecasts are made before a new product (category) is launched in a given country (local launch) but has already been launched in other countries.

3.2.1. Forecasts before the first international launch

Before a new product (category) is launched for the first time, we predict its penetration in country \(i\) at duration time \(t\) (i.e., \(t\) years after launch) as the value at \(t\) of the segment-specific curve to which country \(i\) belongs. Forecasts can be obtained for all prediction horizons in this fashion. In the case of dynamic segments, the set of similar countries used to build forecasts changes over the product life cycle as segment membership becomes time-varying. If the segmentation is probabilistic, as it is for our proposed HMM, the predicted curve for the focal country \(i\) refers to a weighted average of all segment-specific curves. That is,

\[
\hat{y}_{i,t} = \sum_{s=1}^{S} w_{st} \hat{f}_{s,t},
\]

where \(\hat{f}_{s,t}\) is the estimate of the segment-specific curve for segment \(s\). The weights \(w_{st}\) are the posterior probabilities that the focal country \(i\) belongs to the given segment at the corresponding time \(t\); so \(w_{st} = P(s(t) = s|y_1,...,y_T)\) results from the EM algorithm.

3.2.2. Forecasts before local launch

Companies often make use of waterfall entry strategies by spreading national introductions over a given time span. In this context, it is possible to use experience from previously entered markets to improve our forecasts. Specifically, in cases where the focal country \(i\) is not the first international entry and the product (category) \(j_0\) has been introduced in similar countries (i.e., in countries belonging to the same segment), we make forecasts in focal country \(i\) using the penetration data of the other member countries of the segment. Again, with dynamic segments, the set of similar countries used to build forecasts changes over the product life cycle. We denote \(\hat{y}_{i,t}\) as the average penetration level in all previously entered countries that belongs to segment \(s\) for product \(j_0\), and for which data are available at time \(t\). We predict the penetration of product \(j_0\) in country \(i\) at time \(t\) as the following weighted average:

\[
\hat{y}_{i,t} = \sum_{s=1}^{S} w_{st} \hat{y}_{st},
\]

where the weights are defined as in Eq. (6).

3.3. Benchmarks

We evaluate the fit and forecasting performance of our semiparametric hidden Markov model for dynamic segmentation against a number of benchmarks. Benchmarks are chosen to allow us to assess the contribution of each of the following dimensions characterizing our approach:

(i) Semiparametric vs. parametric response model;
(ii) Multi-country vs. single-country segments;
(iii) Model-based vs. a priori-defined segmentation;
(iv) Dynamic vs. static segments.

The various benchmarks are listed in Table 1 and are subsequently described in turn.

3.3.1. Semiparametric vs. parametric response model

First, we assess whether our semiparametric spline-based HMM yields a better fit and forecasting performance than a parametric variant. To do so, we replace the segment-specific and product-deviation response functions in Eq. (1) with parametric equivalents. We use the Bass (1969) mixed-influence model. For completeness, we also implement each of the methods below in a parametric and semiparametric
way, allowing us to assess the systematic contribution of the $p$-splines approach through all the approaches.

3.3.2. Multi-country vs. single-country segments

Second, we assess whether grouping countries into segments (multi-country segments) yields a better fit and forecasting performance than considering each country as a separate segment (single-country segments). A so-called single-country segments model with one country per segment can be represented by Eqs. (3) and (4), where the segment-specific parameters are replaced by country-specific parameters. A parametric and a semiparametric version are considered. Note that the parametric version is equivalent to the multi-product, multi-country, Bass model proposed by Talukdar et al. (2002) without covariates. The resulting segmentations are static, as the segmentation membership is constant over time.

3.3.3. Model-based vs. a priori-defined segmentation

Third, we assess whether model-based segmentation yields a better fit and forecasting performance than a-priori segmentation. To do so, we replace the segment-specific parameters in Eqs. (3) and (4) with geographic region indices, yielding a priori-defined segments. We follow the geographic classification established by the United Nations Statistics Division: Africa, southeast Asia, eastern Europe, Latin America, the Middle East (Western, Central and Southern Asia), North America, Oceania, and western Europe. Table 2 depicts a list of all countries in our study by geographic region. Segments are static as the segmentation membership is constant over time.

3.3.4. Dynamic vs. static segments

Fourth, we assess the relevance of allowing for segment dynamics by comparing the proposed hidden Markov models to finite-mixture models, further denoted as static segments. Countries were not allowed to change segment membership over time. We implement both a parametric finite-mixture Bass model, as proposed by Helsen et al. (1993), and a semiparametric finite-mixture splines model, along the same lines as the functional clustering approach suggested by James and Sugar (2003).

Note that all the models are implemented within the same framework. The parametric models are obtained by replacing the segment (and product) curves in Eq. (1) with the Bass diffusion function, depending on three segment- and product-specific parameters. The single-country segments approach corresponds to $S = N$ segments (i.e., each country is a single segment). The a-priori segmentation approach replaces the probabilities in Eq. (2) with an indicator of the known cluster membership. Finally, the finite-mixture model is a special case of the HMM, where the transition matrix is diagonal. In total, 8 different models are obtained that represent all possible cases. Note that we do not need a full factorial design of $2^9$ combinations because the 8 omitted combinations of factors are impossible cases (e.g., single-country segments are, by nature, neither model-based segments nor dynamic, and a priori-defined segments are also not dynamic). When the segmentation is model-based, the number of segments, as reported in the second column of Table 5, is selected according to the BIC criterion.

4. Data

We gathered annual data on the percentage penetration of six new product categories among households in 79 countries. The data source is Euromonitor. The new product categories are ICT products and media devices, and we therefore expect them to exhibit similarities in their penetration patterns. The products include CD players, DVD players (including DVD recorders), home computers, Internet subscriptions, and so on. We use data from 2002 to 2006.

Table 1

<table>
<thead>
<tr>
<th>Models</th>
<th>Semiparametric vs. parametric response model</th>
<th>Multi-country vs. single-country segments</th>
<th>Model-based vs. a priori-defined segmentation</th>
<th>Dynamic vs. static segments</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Benchmarks</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Single-country segments</td>
<td>Parametric</td>
<td>Single-country</td>
<td>A priori</td>
<td>Static</td>
</tr>
<tr>
<td>A priori-defined segments (geographic regions)</td>
<td>Parametric</td>
<td>Multi-country</td>
<td>Multi-country</td>
<td>Static</td>
</tr>
<tr>
<td>Static segments</td>
<td>Semiparametric</td>
<td>Multi-country</td>
<td>Multi-country</td>
<td>Static</td>
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<tr>
<td>Dynamic segments</td>
<td>Parametric</td>
<td>Multi-country</td>
<td>Multi-country</td>
<td>Dynamic</td>
</tr>
</tbody>
</table>

Table 2

<table>
<thead>
<tr>
<th>Africa</th>
<th>Asia</th>
<th>Eastern Europe</th>
<th>Latin America</th>
<th>Middle East</th>
<th>North America</th>
<th>Oceania</th>
<th>Western Europe</th>
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</thead>
<tbody>
<tr>
<td>Algeria</td>
<td>Cameroon</td>
<td>China</td>
<td>Hong Kong</td>
<td>Belarus</td>
<td>Bosnia Herz.</td>
<td>Argentina</td>
<td>Azerbaijan</td>
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<td>Egypt</td>
<td>Morocco</td>
<td>Nigeria</td>
<td>South Africa</td>
<td>Tunisia</td>
<td>Philippines</td>
<td>South Korea</td>
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mobile phones, and cable television. As we define penetration as the number of devices or subscriptions used by a population divided by the number of users (member households or individuals), penetration could exceed 100% (i.e., when users own multiple devices) and could decrease over time (i.e., when users disadopted products). The set of 79 countries (see Table 2) is global, consisting of western and eastern European countries, North American and Latin American countries, and African and Middle Eastern countries, and thus contains both developing and developed countries, as recommended by Burgess and Steenkamp (2006).

The database covers the period from 1977 to 2009. Because the various technologies are introduced at different times during this period, the starting date of each series differed across product categories and countries. Note that we observe a maximum of 25 years of data per product-country combination. Several technologies had presumably not reached half of their market potential in 2009, as there is no inflection point within the data range. In total, we obtain data on 398 product-country combinations. We achieve full country coverage for DVD players, Internet subscriptions and home computers while some countries are missing data for CD players, mobile phones and cable television.

5. Results

In this section, we first present the results of the dynamic segmentation model applied to the aforementioned set of new product categories. Next, we demonstrate the superior fit and forecasting accuracy of the dynamic segmentation method as compared with the benchmark methods introduced above.

5.1. Dynamic country segments in new product growth

We estimate the semiparametric hidden Markov model for various numbers of segments. To determine the appropriate number of segments, we compute various model performance statistics (see the methodology section), including (i) the overall fit using the Bayesian information criterion (BIC), (ii) the separability of the segments using the normalized entropy criterion (NEC) and (iii) the stability of the segmentation solution using the adjusted Rand index (ARI). All results are reported in Table 3. The lowest BIC and NEC are obtained using a 3-segment solution. For the ARI, the 2-segment and 3-segment solutions yield the highest stability to changes in the data. Therefore, we opt for the 3-segment solution.

Fig. 2 shows the segment-specific penetration pattern for these three latent segments. We subsequently label the segments according to the level of the dependent variable as “low-penetration” (segment 1), “mid-penetration” (segment 2) and “high-penetration” (segment 3) segments. The low-penetration segment exhibits slow growth over the complete time range, with penetration levels reaching about 40% of the households 25 years after introduction. The mid-penetration segment shows a higher growth rate than the low-penetration segment, especially when the product category has been on the market for more than 8 years. Finally, the high-penetration segment shows a substantially faster and higher diffusion rate over the complete time range than the other two segments. Penetration in the high-penetration country segment accounts for 80% of the households after 25 years.

To assess the reliability of the estimates of the segment-specific functions, we use the parametric bootstrap procedure described in Zucchini and MacDonald (2009, p. 55). The bootstrap procedure captures the uncertainty in both the segment membership and the estimation of the segment-specific curves. We obtain an estimate of the covariance matrix of the estimator and compute the standard error of the difference between each pair of estimated curves. The resulting t-statistic values over the product life cycle (see the Appendix) confirms that the high-penetration segment exhibits consistently higher penetration levels than the other segments over the complete time range while the low- and mid-penetration segment curves only became significantly different from each other once 8 years has passed since the introduction of the product. At the early stages of diffusion, the information in the data is still too scarce to be able to clearly distinguish segments; penetration is low in both segments. These findings are presented in Table 4, where the transition probabilities between these two segments are greater than 40% during the first 5 years after launch. In time, these two segments become more distinct. This phenomenon is also shown in Table 4, where we can see that the transition probabilities decrease between 6 and 15 years after introduction.

![Fig. 2. Segment-specific penetration patterns of the high-, mid- and low-penetration segments.](image)

Table 3

<table>
<thead>
<tr>
<th>Number of segments (S)</th>
<th>Bayesian Information Criterion (BIC)</th>
<th>Normalized Entropy Criterion (NEC)</th>
<th>Adjusted Rand Index (ARI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>41,818</td>
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<td>2</td>
<td>38,111</td>
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<td>3</td>
<td>36,187</td>
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<td>4</td>
<td>39,441</td>
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<td>5</td>
<td>46,049</td>
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<td>6</td>
<td>48,127</td>
<td>0.17</td>
<td>0.04</td>
</tr>
</tbody>
</table>

From t = 1 to 5 years after introduction:

<table>
<thead>
<tr>
<th>Segment 1</th>
<th>Segment 2</th>
<th>Segment 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>52.06% [0.08]</td>
<td>41.70% [0.03]</td>
<td>6.24% [0.06]</td>
</tr>
<tr>
<td>40.89% [0.04]</td>
<td>54.12% [0.08]</td>
<td>4.98% [0.07]</td>
</tr>
<tr>
<td>1.68% [0.03]</td>
<td>1.66% [0.03]</td>
<td>96.66% [0.06]</td>
</tr>
</tbody>
</table>

From t = 6 to 15 years after introduction:

<table>
<thead>
<tr>
<th>Segment 1</th>
<th>Segment 2</th>
<th>Segment 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>91.42% [0.18]</td>
<td>8.55% [0.18]</td>
<td>0.03% [0.00]</td>
</tr>
<tr>
<td>8.94% [0.18]</td>
<td>91.03% [0.19]</td>
<td>0.02% [0.00]</td>
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<tr>
<td>0.00% [0.00]</td>
<td>0.00% [0.00]</td>
<td>100.00% [0.00]</td>
</tr>
</tbody>
</table>

From t = 16 to T years after introduction:

<table>
<thead>
<tr>
<th>Segment 1</th>
<th>Segment 2</th>
<th>Segment 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>82.63% [0.04]</td>
<td>17.37% [0.04]</td>
<td>0.00% [0.00]</td>
</tr>
<tr>
<td>16.79% [0.05]</td>
<td>83.21% [0.05]</td>
<td>0.00% [0.00]</td>
</tr>
<tr>
<td>0.00% [0.00]</td>
<td>0.00% [0.00]</td>
<td>100.00% [0.00]</td>
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</tbody>
</table>
Specific to our dynamic segmentation approach, we observe countries changing segments over the life cycle of the product. These changes are governed by the time-varying transition probability matrices. Table 4 reports the average transition probabilities (in percentages) between segments during three consecutive time spans: year 1 to year 5, year 6 to year 15, and year 16 to year 25. The matrices provide information on the stickiness in each segment over time. In particular, diagonal elements indicate how likely countries are to remain in the same segment over the product life cycle. In contrast, the nondiagonal elements capture the existing dynamics in segment membership. We find that the dynamic nature of the international market segmentation of a new product is most pronounced at the beginning of the product life cycle. When product categories became more mature, the dynamic nature of segment membership decreased. Compared with the low- and mid-penetration segments, the high-penetration segment shows little dynamics. Most segment changes occur between the low- and mid-penetration segments, and most changes occur between neighboring segments (e.g., between segments 1 and 2 but rarely between segments 1 and 3).

As countries switch segments over the product life cycle, segment membership probabilities evolve, as depicted by Fig. 3. Fig. 3 reports the evolution of the prior membership probabilities among the three segments. Interestingly, we find that the high-penetration segment (segment 3) is small in terms of the number of members during the first years of the product life cycle and gradually increases in size as the product categories mature. In contrast, the low-penetration segment is initially the largest segment and gradually loses members over time. Finally, the size of the mid-penetration segment is much less variable. For mature product categories, country segments display similar sizes. Beyond the prior segment membership probabilities, we also estimate the time-varying posterior segment membership probabilities per country for each country in our data (i.e., the probability of each country i belonging to segment s at time t). Fig. 4 reports these membership probabilities among 6 leading industrial nations: the USA, the United Kingdom, Japan, Germany, France and Italy. Fig. 5 reports these probabilities among 6 leading emerging markets, often referred to as the BRICS + M countries: Brazil, Russia, India, China, South Africa and Mexico. Collectively, these 12 countries capture more than half of the global population and economic activity.

Figs. 4 and 5 clearly illustrate how countries stochastically switch between segments over time and allow the reader to visualize the most likely state path of each country. In general, we observe three different types of paths in our data set. Some countries belong with a very high probability to the high-penetration segment over the complete time span (except perhaps for the first few years after product introduction) and therefore display little membership dynamics over time. This is true for the 6 leading industrial nations in Fig. 4 and also for most western European countries (Austria, Belgium, Finland, Ireland, the Netherlands, Norway, Portugal, Spain, Sweden and Switzerland); Canada; Australia and New Zealand; and the most developed southeast Asian and Middle East nations (Bahrain, Hong Kong, Israel, Kuwait, South Korea, Taiwan, and the United Arab Emirates).

Another set of countries tend to switch between the low- and mid-penetration segments during the first 6–7 years after product introduction and subsequently settle in the mid-penetration segment in later periods. These countries include Russia, China and South Africa in Fig. 5, and they also include many eastern European countries (Bosnia-Herzegovina, Bulgaria, the Czech Republic, Estonia, Hungary, Lithuania, and Slovenia) and several other nations from the Middle East, southeast Asia (Kazakhstan, Qatar, Saudi Arabia) and Latin America (Columbia and Costa Rica).

A final set of countries show comparable probabilities to belong to (and therefore tend to switch between) the low- and mid-penetration segments during the first 6–7 years after product introduction but then tend to subsequently remain in the low-penetration segment. These countries include Brazil, India and Mexico in Fig. 5; several less-developed or developing economies from various parts of the world, mostly Latin American countries (Argentina, Chile, the Dominican Republic, Peru and Venezuela) and many African countries (Algeria, Cameroon, Egypt, Morocco, Nigeria, and Tunisia); some eastern European countries (Belarus, Croatia, Georgia, Poland, Romania, Slovakia and Ukraine), and Asian (Indonesia, Philippines and Vietnam) and Middle Eastern countries (Iran, Jordan, Pakistan, Turkey and Turkmenistan). Our results are in line with the findings of Dekimpe et al. (2000), Van den Bulte and Stremersch (2004), and Van Everdingen et al. (2009), among others, who find the adoption timing of new products to be negatively correlated with Gross Domestic Product.

To conclude the investigation of our results, we compare the fit of our dynamic segmentation model with the alternative specifications described in section 3.3 and summarized in Table 1. In Table 5, we report the Bayesian Information Criterion (BIC), the log-likelihood and the number of segments chosen for each model. First, our results show that a semiparametric specification leads to a better fit performance than its parametric counterpart in terms of BIC. The flexibility of semiparametric models paid off. The only exception is for the single-country segments approach because the BIC penalizes for the high number of country-specific parameters involved in the semiparametric model. However, the fit performance of the single-country segments models remains inferior to the performance of all multi-country segments models.

Second, our results clearly indicate that the model-based segmentation approaches (i.e., the static and dynamic segments) outperform in fit the a priori-defined regional segments, both for the parametric and semiparametric versions. Such findings support the current knowledge in marketing research that domain-based segmentation bases should be favored over general segmentation bases (Steenkamp & Ter Hofstede, 2002).

Third, the fit comparison also shows that the semiparametric dynamic segmentation approach yields the best fit performance of all specifications.

To conclude, our proposed semiparametric dynamic segmentation approach demonstrates better in-sample fit than the other models. In the next section, we will assess the hold-out predictive performance of our approach.

5.2. Prelaunch predictive performance

We assess the relative predictive performance of the dynamic segmentation model against the alternative approaches described in section 3.3. The prediction task consists of forecasting the future
penetration levels reached by a new product category in each country before its launch time in this country. All forecasts are made prior to the product introduction and for various prediction horizons (further denoted \(h\)), where \(h\) ranges from 1 year to 5 years after launch (i.e., 5 years-ahead forecasts).

For forecasts made before the first international launch, no information on the actual adoption of the new product is available yet. If we denote \(t_{ij}\) as the year when a new product \(j_0\) is introduced in country \(i\), the estimation sample to forecast penetration of product \(j_0\) in country \(i\) at prediction horizon \(h\) only includes the penetration data of other products available prior to \(t_{ij}\). In other words, we cut our data sample according to the calendar time at \(t_{ij}\). All data corresponding to the years after product \(j_0\) has been launched in country \(i\) do not belong in the estimation sample.

For subsequent entries (all countries entered after the first country entered), some information on the actual adoption of the product became available. More specifically, the estimation sample to predict the penetration of a new product \(j_0\) in a subsequent entry \(i'\) at prediction horizon \(h\) also includes the penetration data on product \(j_0\) in previously-entered countries up to the introduction time in the focal country \(i'\). We use the penetration of product \(j_0\) in the focal country for all available years as a hold-out sample. Thus, for each product-country combination, we construct a different estimation and hold-out sample, divided according to calendar time. This framework replicates the data context practitioners face when making pre-launch forecasts.

Because the goal is to use the penetration data of older product categories to forecast the penetration of new product categories, we focus in the analysis on the most recent product categories in our data set, DVD players and Internet, which were both introduced in the 1990s. We assess the predictive accuracy of each method by computing the mean absolute deviation (MAD) between the predicted value and the actual value across all countries per prediction horizon. Table 6 reports the average MAD of the prelaunch forecasts for all methods per product category over various prediction horizons, from \(h = 1\) to \(h = 5\). In practical terms, the MAD can be interpreted as the average absolute deviation from the actual penetration level. For instance, a MAD = 1.00 indicates that our forecasts deviate from the actual penetration level by 1.00 unit. If the actual penetration is 20% of households, the corresponding forecast averages between 19% and 21% of households. The best method is reported in bold for each product category. Note that in Table 6, the results for the forecasts made before the first international launch and before a local launch are lumped together to compute the MAD.

The out-of-sample forecasting comparison supports four main conclusions. First, semiparametric models give more accurate forecasts than parametric models based on the Bass specification. Second, relying on multi-country segments rather than single countries generally improves prelaunch forecasts, indicating that segmentation allows for the identification of similar countries and can help the analyst decide how to account for data available from other countries. Information is thus gained by pooling across countries. For DVD players, forecasts made at the multi-country segment level mostly outperform forecasts made using country-specific information from one country only. For Internet subscriptions, this is also the case for the semiparametric models while all parametric models perform quite poorly. Third, we do not find substantial differences in forecasting performance between the a priori-defined segments and the static model-based segments. Fourth, dynamic segments yield better forecasts than static segments, confirming that there are substantial dynamics in country segment membership, which the static segmentation approach do not account for.

Fig. 4. Dynamic segment membership probability path for 6 leading industrial nations: USA, United Kingdom, Japan, Germany, France and Italy. Labels indicate (1) the low-penetration segment, (2) the mid-penetration segment and (3) the high-penetration segment.
In practical terms, our dynamic segmentation method yields low average absolute forecast deviations both for DVD players and Internet subscriptions. For the former, we find that our forecasts deviate by only .64 units (i.e., 0.64% of the households in the country) from the actual penetration levels 5 years after introduction. For Internet subscriptions, the dynamic segmentation yields forecasts that deviate by 2.22 units (i.e., 2.2% of the households in the country) on average from the actual penetration level 5 years after introduction.

In sum, the semiparametric dynamic segmentation approach offers the lowest forecast errors for all prediction horizons for both product categories, suggesting that country segments show substantial dynamics and that the flexible semiparametric specification of the penetration pattern is appropriate. These results are particularly encouraging given that the forecast of the first five years after launch is probably the most crucial for managers when they plan to launch a new product on the market.

### 6. Conclusions and discussion

Recent calls in the marketing literature have highlighted the need for a dynamic modeling framework when approaching nonstationary marketing phenomena (e.g., Lemmens, Croux, & Dekimpe, 2007; Pauwels et al., 2004), such as new product adoption. Furthermore, in the country segmentation literature, Steenkamp and Ter Hofstede (2002) have cautioned that the static nature of the current international segmentation methods limits their usefulness.

In this paper, we apply a new dynamic segmentation methodology, based on semiparametric modeling, to six new product categories in 79 countries and show that, in this sample, country segmentation in new product growth is dynamic and not static. Our approach makes it possible to identify markets that are homogeneous during a given part of the product life cycle. We find that country segment membership varies over the product life cycle and that accounting for this time variation provides superior prelaunch forecasts. Therefore, we recommend that international firms and public policy bodies (e.g., the European Commission and the United Nations) that have a stake in understanding cross-national differences in innovativeness and in making global forecasting reports reconsider their current practice. These entities should adopt a dynamic segmentation approach instead of an exogenously defined regional segmentation approach or a static model-based segmentation approach. In so doing, they should also cautiously consider the set of products or product categories to use as a reference (i.e., the estimation sample) when deriving dynamic segments. This choice is likely to affect the outcome of the segmentation and should therefore be made with

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### Table 5

Model fit comparison.

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Number of segments</th>
<th>BIC</th>
<th>Log-likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Parametric models</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single-country segments</td>
<td>79</td>
<td>58,198</td>
<td>−21,680</td>
</tr>
<tr>
<td>A priori-defined segments</td>
<td>8</td>
<td>48,058</td>
<td>−23,643</td>
</tr>
<tr>
<td>(geographic regions)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Static segments</td>
<td>4</td>
<td>44,601</td>
<td>−21,926</td>
</tr>
<tr>
<td>Dynamic segments</td>
<td>2</td>
<td>44,712</td>
<td>−22,060</td>
</tr>
<tr>
<td><strong>Semiparametric models</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single-country segments</td>
<td>79</td>
<td>70,211</td>
<td>−11,808</td>
</tr>
<tr>
<td>A priori-defined segments</td>
<td>8</td>
<td>41,118</td>
<td>−18,866</td>
</tr>
<tr>
<td>(geographic regions)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Static segments</td>
<td>4</td>
<td>36,331</td>
<td>−17,125</td>
</tr>
<tr>
<td>Dynamic segments</td>
<td>3</td>
<td>36,187</td>
<td>−16,883</td>
</tr>
</tbody>
</table>

---

Fig. 5. Dynamic Segment Membership Probability Path for 6 Leading Emerging Markets: Brazil, Russia, India, China, South Africa and Mexico. Labels indicate (1) the low-penetration segment, (2) the mid-penetration segment and (3) the high-penetration segment.
Table 6
Prelaunch mean absolute forecast errors (MAD) per product in the hold-out sample, for various prediction horizons from \( h = 1 \) to \( h = 5 \) for all models*.

<table>
<thead>
<tr>
<th>DVD Players</th>
<th>( h = 1 )</th>
<th>( h = 2 )</th>
<th>( h = 3 )</th>
<th>( h = 4 )</th>
<th>( h = 5 )</th>
</tr>
</thead>
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<tr>
<td>Parametric models</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single-country segments</td>
<td>0.78</td>
<td>1.14</td>
<td>1.49</td>
<td>1.83</td>
<td>2.15</td>
</tr>
<tr>
<td>A priori-defined segments</td>
<td>0.52</td>
<td>0.85</td>
<td>1.30</td>
<td>1.80</td>
<td>2.45</td>
</tr>
<tr>
<td>Static segments</td>
<td>0.43</td>
<td>0.70</td>
<td>1.20</td>
<td>1.76</td>
<td>2.55</td>
</tr>
<tr>
<td>Dynamic segments</td>
<td>0.37</td>
<td>0.71</td>
<td>1.22</td>
<td>1.77</td>
<td>2.44</td>
</tr>
<tr>
<td>Semiparametric models</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single-country segments</td>
<td>0.68</td>
<td>1.00</td>
<td>1.32</td>
<td>1.68</td>
<td>2.04</td>
</tr>
<tr>
<td>A priori-defined segments</td>
<td>0.27</td>
<td>0.45</td>
<td>0.75</td>
<td>1.07</td>
<td>1.48</td>
</tr>
<tr>
<td>Static segments</td>
<td>0.28</td>
<td>0.45</td>
<td>0.72</td>
<td>1.05</td>
<td>1.49</td>
</tr>
<tr>
<td>Dynamic segments</td>
<td>0.15</td>
<td>0.23</td>
<td>0.32</td>
<td>0.48</td>
<td>0.64</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Internet Subscribers</th>
<th>( h = 1 )</th>
<th>( h = 2 )</th>
<th>( h = 3 )</th>
<th>( h = 4 )</th>
<th>( h = 5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parametric models</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single-country segments</td>
<td>0.80</td>
<td>1.11</td>
<td>1.41</td>
<td>1.87</td>
<td>2.58</td>
</tr>
<tr>
<td>A priori-defined segments</td>
<td>0.00</td>
<td>0.35</td>
<td>2.27</td>
<td>3.12</td>
<td>4.03</td>
</tr>
<tr>
<td>Static segments</td>
<td>0.00</td>
<td>1.58</td>
<td>2.72</td>
<td>3.72</td>
<td>4.75</td>
</tr>
<tr>
<td>Dynamic segments</td>
<td>0.00</td>
<td>1.16</td>
<td>1.86</td>
<td>2.43</td>
<td>3.06</td>
</tr>
<tr>
<td>Semiparametric models</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single-country segments</td>
<td>0.68</td>
<td>1.00</td>
<td>1.25</td>
<td>1.62</td>
<td>2.22</td>
</tr>
<tr>
<td>A priori-defined segments</td>
<td>0.00</td>
<td>0.65</td>
<td>1.11</td>
<td>1.66</td>
<td>2.42</td>
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<tr>
<td>Static segments</td>
<td>0.00</td>
<td>0.66</td>
<td>1.19</td>
<td>1.84</td>
<td>2.68</td>
</tr>
<tr>
<td>Dynamic segments</td>
<td>0.00</td>
<td>0.33</td>
<td>0.69</td>
<td>1.31</td>
<td>2.22</td>
</tr>
</tbody>
</table>

* The lowest mean absolute deviations (MAD) are given in bold.

care. In our data, we find a substantial amount of heterogeneity across products, which we captured by using the product-deviation function.

Our research can be extended in multiple ways. First, our dynamic segmentation is done at the aggregate level, and our method identifies countries, rather than consumers, that share similar penetration patterns. Country-level analysis conveys a number of advantages, such as the excellent availability of data at the country level and the good accessibility and cost-effectiveness achieved through centralization of the resulting country segments. However, country segments also suffer from a number of limitations. They overlook the differences that exist between consumers within these countries and ignore the potential horizontal consumer segments that cross national borders. Country segments also tend to be less responsive to marketing efforts than disaggregated consumer segments (Steenkamp & Ter Hofstede, 2002). An interesting avenue for future international marketing efforts than disaggregated consumer segments (Steenkamp & Ter Hofstede, 2002). An interesting avenue for future international marketing efforts than disaggregated consumer segments (Steenkamp & Ter Hofstede, 2002).

Second, our approach makes an abstraction of the role of country-specific and product-specific characteristics that might partially underlie the diffusion processes. For example, the observed penetration level in one country may be influenced by the adoption of a product in neighboring countries (e.g., cross-country spillover effects and lead-lag effects). Similarly, influences can also occur between products, as could occur in the presence of competitive or substitution effects for multigenerational technologies (Islam & Meade, 2010). While such effects are outside the scope of the present research, it would be a fruitful research goal to study their role in diffusion by including them at two levels of the hidden Markov model: (i) in the response component of the HMM as additional covariates and/or (ii) in the specification of the transition probabilities, in the same manner as proposed by Netzer et al. (2008).

Third, we show that country segments are intrinsically dynamic, but the question remains how the complexity of the segments that these methods yield can be absorbed by managerial practice. Therefore, more research is needed to understand how organizations could align themselves to have more dynamic international structures.

Overall, our dynamic segmentation framework opens multiple opportunities to tackle nonstationary phenomena in marketing where segmentation is needed. As the increasing number of studies in this area testifies, modeling marketing dynamics will clearly be one of the important research areas in marketing science in the next decade.

Appendix

Value of the t-statistic for testing the equality between every pair of segment-specific curves over time. The horizontal line is the 5% critical value.

References

Beyond expectations: The effect of regulatory focus on consumer satisfaction

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A B S T R A C T

This paper examines the effect of regulatory focus on consumer satisfaction. In contrast to the disconfirmation of expectations model of satisfaction, we find that, although regulatory focus does affect consumers’ expectations, the effect on satisfaction cannot be explained by differences in those expectations. Instead, our results reveal a direct effect of consumers’ regulatory focus on satisfaction that is based on the conservative bias of prevention-focused consumers. Compared to promotion-focused consumers, prevention-focused consumers protect against making errors and demonstrate a conservative bias in their evaluations of satisfaction. The results of two experiments demonstrate this conservative bias, showing that, compared to promotion-focused consumers, prevention-focused consumers are less satisfied with positive outcomes and more satisfied with negative outcomes.

1. Introduction

Marketers have traditionally described consumer decision making as a series of five progressive stages: need recognition, information search, evaluation of alternatives, purchase decision, and post-purchase processes (e.g., Grewal & Levy, 2010). In recent years, regulatory focus theory has extended our knowledge of consumer decision making by investigating the effect of promotion and prevention orientations on consumer information search (Pham & Chang, 2010), information processing (e.g., Aaker & Lee, 2001; Bosmans & Baumgartner, 2005; Kirmani & Zhu, 2007; Pham & Avnet, 2004), and choice (Briley & Wyer, 2002; Wang & Lee, 2006).

In the last twenty-five years, researchers have also learned a great deal about consumer satisfaction. For example, we know that satisfied customers are often of greater value because they tend to spend more money, exhibit higher levels of loyalty, and talk more favorably about a product to others (for a review see Vargo, Nagaio, He, & Morgan, 2007). In addition, there has been a great deal of support for the disconfirmation of expectations model of satisfaction, which contends that consumers’ pre-purchase expectations are a key driver of their ultimate satisfaction (Bolton & Drew, 1991; Oliver, 1980, 1997; Parasuraman, Zeithaml, & Berry, 1994).

However, the literature is noticeably silent on how consumers’ regulatory focus affects satisfaction in the post-purchase stage of consumer decision making. The present paper takes a first step towards addressing this issue by examining the impact that promotion and prevention orientations have on consumer satisfaction. In contrast to the disconfirmation of expectations model of satisfaction, we contend that a consumer’s regulatory focus can have a direct effect on satisfaction that is independent of expectations. Specifically, based on the conservative bias of prevention-focused consumers, which has been demonstrated in prior research (Crowe & Higgins, 1997; Higgins, 2002), we predict that prevention-focused consumers will be more satisfied with a negative outcome and less satisfied with a positive outcome than promotion-focused consumers. In the following sections, we discuss the theoretical rationale for the impact of regulatory focus on satisfaction and present the method and results of two experimental studies that document this effect. The paper concludes with a discussion of the theoretical and practical implications of our findings.

2. Theory development

Higgins (1987) suggests that there are two fundamental goal classifications that dominate human behavior: ideals and oughts. Ideals refer to people’s hopes, wishes and aspirations (e.g., owning a sports car), whereas oughts refer to people’s obligations, duties and responsibilities (e.g., taking care of one’s family). Ideals and oughts are pursued using different self-regulatory systems. Ideals are pursued with
the promotion system, while oughts are pursued using the prevention system (Higgins, 1997, 1998). Thus, regulatory focus theory suggests fundamental motivational differences in the goals that each system regulates (Higgins, 1997, 1998, 2002). Promotion-focused consumers are concerned with goals of growth and advancement, while prevention-focused consumers are concerned with goals of security and responsibility.

Promotion and prevention are also distinct in the types of strategies that these systems activate in the pursuit of goals (Higgins, 1997; Pham & Avnet, 2004). Promotion-focused consumers approach gains and avoid non-gains. Their goal pursuit is characterized by eagerness and a desire to approach accomplishments. In contrast, people with a prevention focus approach non-losses and avoid losses. Their goal pursuit is characterized by vigilance and a desire to avoid making mistakes. As a result, those with a prevention focus are more sensitive to losses. Therefore, relative to people who are promotion-focused, individuals with a prevention focus tend to exhibit a conservative bias in judgment and decision making (Crowe & Higgins, 1997; Higgins, 2002). This conservative bias was tested in a memory recognition task by Crowe and Higgins (1997) in which participants were presented with an initial list of 20 letter strings (non-sense words). Next participants were presented with a second list of 40 letter strings. Of the 40 letter strings, 20 of the letter strings were in the initial list, and 20 of the letter strings were new. Participants then responded as to whether they had previously seen the letter string. The results revealed that, compared with promotion-focused participants, prevention-focused participants protected against making mistakes, demonstrating a conservative bias by saying “no” (Crowe & Higgins, 1997).

Consumer research has documented the effects of promotion and prevention in a variety of different domains, including information search (Pham & Chang, 2010), information processing (e.g., Aaker & Lee, 2001; Bosmans & Baumgartner, 2005; Kirmani & Zhu, 2007; Pham & Avnet, 2004) and preference formation (Briley & Wyer, 2002; Wang & Lee, 2006). The research presented in this article contributes to this literature by demonstrating that consumers’ regulatory focus can also influence their satisfaction with a consumption experience. We contend that the conservative bias among people with a prevention focus, relative to those with a promotion focus, has important implications for consumer satisfaction. Specifically, a prevention focus should lead people to protect against making errors, resulting in more reserved and conservative evaluations. Therefore, we predict that, as compared to promotion-focused consumers, prevention-focused consumers will be less satisfied by positive outcomes and more satisfied by negative outcomes.

From the perspective of regulatory focus theory, this prediction is a relatively straightforward implication of the conservative bias that previous research has identified among people who are prevention-focused (Crowe & Higgins, 1997; Higgins, 2002). However, regulatory focus theory suggests a direct effect of regulatory focus on satisfaction that does not rely on the expectations that a consumer has for the consumption experience. This prediction is not easily accounted for by the well-established disconfirmation of expectations model (Oliver, 1980, 1997), which contends that satisfaction and dissatisfaction arise from a cognitive process whereby pre-purchase expectations are compared to the actual consumption experience. The result of this comparison leads to expectancy disconfirmation — positive disconfirmation when the outcome is better than expected and negative disconfirmation when the outcome is worse than expected.

Nevertheless, despite the large body of evidence supporting the disconfirmation of expectations model of satisfaction (e.g., Bolton & Drew, 1991; Oliver, 1980, 1997; Parasuraman et al., 1994), other researchers have argued that, at least in some situations, expectations and satisfaction can operate independently (e.g., Westbrook & Reilly, 1983). In the two experiments that follow, we test our prediction that prevention-oriented consumers are less satisfied than promotion-focused consumers with positive outcomes and more satisfied with negative outcomes. In contrast to the disconfirmation of expectations model of satisfaction, we find that although regulatory focus does affect consumers’ expectations, the effect on satisfaction cannot be explained by differences in those expectations. Instead, our results reveal a direct effect of consumers’ regulatory focus on satisfaction, which is consistent with the conservative bias of prevention-focused consumers that has been demonstrated in prior research (Crowe & Higgins, 1997; Higgins, 2002).

3. Experiment 1

3.1. Method

3.1.1. Participants and design

A total of 103 participants were randomly assigned to the conditions of a 2 (consumption experience: positive vs. negative) by 2 (regulatory focus: promotion vs. prevention) between-subjects design. Participants were selected from the subject pool of a large North American university; participants received partial course credit for their participation.

3.1.2. Procedure

The experiment was administered as two unrelated studies. In the first study, the participants completed a priming task. Following Pham and Avnet (2004), we used a priming procedure to manipulate participants’ regulatory focus. In the promotion condition, we used an ideals prime that required participants to think about their past hopes, aspirations and dreams and then to list two of them. Following this procedure, they were asked to think about their current hopes, aspirations and dreams and then to list two of them. In the prevention condition, we used an oughts prime, which required participants to think about their past duties, obligations and responsibilities and then to list two of them. They were then asked to think about their current duties, obligations and responsibilities and then to list two of them.

In the ostensibly unrelated second study, we measured participants’ satisfaction with a camera’s performance. All participants were provided with a scenario that asked them to choose between two cameras. The cameras were minor purchases in the scenarios and were not expensive ($39).

To establish a basis for expectations, participants were given an average consumer rating from an unbiased source. To induce consistent choice across participants, one camera was rated as objectively superior (the dominant choice among study participants), and the other was rated as objectively inferior (the dominated choice). In a pre-test, 100% of the participants selected the dominant camera. In the main study, five participants chose the inferior camera and, as a result, they were eliminated from the analysis. The final sample had a total of 98 participants.

Next, we measured participants’ expectations of the performance of the camera that they chose using 3 nine-point items anchored by “Average, like most snapshots” and “Excellent, like a professional print” (α = .94) (Spreng & Olshavsky, 1993). The items were (1) “What would be the level of picture quality you would expect from this camera?” (2) “What would be the clarity of picture quality you would expect from this camera?” (3) “What would be the sharpness of picture quality you would expect from this camera?”

The operationalization of positive versus negative product experience was consistent with previous satisfaction research (Spreng, MacKenzie, & Olshavsky, 1996; Voss, Parasuraman, & Grewal, 1998). All subjects viewed the same four pictures; however, the quality of the photos varied between conditions. In the positive product experience condition, the photos were of a consistently higher quality. In the negative product experience condition, clarity and sharpness were manipulated using photo software (Adobe Photoshop 7) to
produce photos that were of consistently poor quality. A pretest confirmed the efficacy of the positive and negative product experience manipulations in a between-subjects design. In the positive experience condition, the overall quality (M = 5.70), clarity (M = 6.40) and sharpness (M = 5.80) were all rated as significantly better than in the negative experience condition, where the overall quality (M = 2.30, F(1, 18) = 32.00, p < .001), photo clarity (M = 2.60, F(1, 18) = 24.61, p < .001), and sharpness (M = 2.70, F(1, 18) = 17.40, p < .001) were consistently lower.

3.1.3. Measures
Satisfaction was measured using three nine-point items anchored by “strongly agree/strongly disagree” or “satisfied/unsatisfied” (α = .97): (1) “Based on these sample photographs, I am satisfied with the camera I chose.” (2) “How satisfied are you with the quality of the photos?” and (3) “How satisfied are you with the performance of the camera?”

3.2. Results

3.2.1. Manipulation checks
As expected, the positive experience photos were rated as being significantly higher on overall picture quality (M = 7.09) than the negative experience photos (M = 3.25, F(1, 96) = 140.40, p < .001). The positive experience photos were rated higher on picture clarity (M = 6.67 vs. M = 2.93; F(1, 96) = 133.72, p < .001) and picture sharpness (M = 6.46 vs. M = 2.75; F(1, 96) = 112.32, p < .001) than the negative experience photos. Thus, the consumption experience manipulation worked as expected.

3.2.2. Expectations
All means, standard deviations, and correlations are presented in Table 1. A two way ANOVA revealed a marginally significant main effect of regulatory focus on expectations: promotion-focused individuals had higher expectations of the camera (M = 5.61) compared to prevention-focused individuals (M = 5.05, F(1, 94) = 3.61, p = .06). As expectations were measured prior to the consumption experience, there should not be an effect of the consumption experience on expectations. Indeed, neither the main effect of the consumption experience, nor the regulatory focus by consumption experience interaction on expectations was statistically significant (ps > .20).

3.2.3. Satisfaction
The effect of the regulatory focus by consumption experience interaction on satisfaction was significant (F(1, 94) = 10.92, p = .001; Fig. 1). In the positive consumption experience condition, when the pictures were good, satisfaction with the camera was lower for participants in the prevention-focused condition (M = 6.89) than it was for participants in the promotion-focused condition (M = 7.81, F(1, 94) = 9.32, p = .03). In the negative experience condition, when the pictures were of poor quality, satisfaction with the camera was higher for participants with a prevention focus (M = 3.67) than for participants with a prevention focus (M = 2.54, F(1, 94) = 9.92, p = .002). As detailed in Table 1, expectations were not correlated with satisfaction.

3.3. Discussion
The results of Experiment 1 demonstrated clear differences in satisfaction between promotion-focused and prevention-focused consumers. Consistent with our theory, prevention-focused consumers were more conservative in their reported level of satisfaction. When the camera’s picture quality was high, prevention-focused consumers were less satisfied than promotion-focused consumers. When the camera’s picture quality was low, prevention-focused consumers were more satisfied than promotion-focused consumers. The results also revealed a marginally significant effect of regulatory focus on expectations; however, there is no correlation between expectations and satisfaction. This is inconsistent with the disconfirmation of expectations model, but it is consistent with our hypothesizing that the effect of regulatory focus on satisfaction is not driven by differences in expectations.

4. Experiment 2
Although participants in Experiment 1 evaluated real photographs, the camera purchase was only hypothetical. To heighten external validity, Experiment 2 was designed to replicate Experiment 1 using a different context in which participants actually consume either high- or low-quality coffee, after being exposed to the same regulatory focus manipulation used in Experiment 1.

4.1. Method

4.1.1. Participants and design
This study employed a 2 (consumption experience: positive vs. negative) by 2 (regulatory focus: promotion vs. prevention) between-subjects design. A total of 120 participants, selected from

<table>
<thead>
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<table>
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<tr>
<th>Study 1: Photos</th>
<th>Promotion</th>
<th>Negative experience</th>
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<tbody>
<tr>
<td>Expectations</td>
<td>5.78 (1.39)</td>
<td>5.45 (1.62)</td>
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<tr>
<td>Satisfaction</td>
<td>7.81 (1.40)</td>
<td>2.54 (1.35)</td>
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<tr>
<td>Correlations: expectations and satisfaction</td>
<td>.46 (p = .01)</td>
<td>.19 (p = .40)</td>
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<tr>
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<th>Prevention</th>
<th>Positive experience</th>
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<td>7.04 (1.31)</td>
</tr>
<tr>
<td>Satisfaction</td>
<td>6.39 (1.23)</td>
<td>3.57 (1.78)</td>
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<tr>
<td>Correlations: expectations and satisfaction</td>
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<td>.07 (p = .70)</td>
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<th>Negative experience</th>
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<td>.21 (p = .37)</td>
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</tr>
</tbody>
</table>

Note: Standard deviations are reported in parentheses for mean ratings.
the subject pool of a large North American university, were randomly assigned to the experimental conditions. The subjects received partial course credit for participation. They were told that they would evaluate a cup of coffee. To establish a basis for expectations, the participants were told that the coffee was a medium-priced, drip-brewed coffee.

The consumption experience was manipulated to be either positive (a hot cup of a premium coffee) or negative (a cup of very weak warm coffee to which baking soda was added). To ensure that our participants had experience with coffee and, therefore, were able to recognize a positive or negative consumption experience—a screening question asking “How much coffee do you drink daily?” was used during the recruitment phase to select only regular coffee drinkers.

The experiment was administered as two unrelated studies. In the first study the participants completed the same priming task used in Experiment 1. In the second study participants were each given a cup containing 6 oz of coffee.

Before participants tasted the coffee, we measured their consumption expectations using three nine-point items anchored by “Bad” and “Excellent” (α = .96) (Spreng & Olshavsky, 1993). The items were (1) “What do you expect the quality of the coffee to be?” (2) “What would you expect the taste of the coffee to be?” and (3) “Overall, I expect this coffee to be good?”

In the positive experience condition, they were served a hot cup of a premium coffee blend. The coffee ranged from 130 to 145 °F in temperature (on average, the preferred temperature for coffee is 140 °F (60 °C); Lee & O’Mahony, 2002). In the negative experience condition, participants were served a very weak, lukewarm cup of coffee to which baking soda had been added—i.e., a non-premium coffee blend was brewed using only 50% of the recommended grounds, a teaspoon of baking soda was added to each 6 ounce cup, and the coffee that was served ranged from 70 to 83 °F in temperature. A pretest confirmed that in the positive experience condition, the coffee tasted better (M = 6.27 on a nine point scale) than in the negative experience condition (M = 3.93, F(1, 28) = 22.93, p < .001). Additionally, in this pretest, the positive experience coffee was also perceived to be of a higher quality (M = 6.33) than the negative experience coffee (M = 3.87, F(1, 28) = 26.04, p < .001). A three-item measure of satisfaction with the coffee revealed higher levels of satisfaction in the positive experience condition (M = 6.17) than in the negative experience condition (M = 4.02, F(1, 28) = 22.97, p < .001).

4.1.2. Measures

Satisfaction was measured using three nine-point items anchored by “satisfied/unsatisfied” and “strongly agree/strongly disagree” (α = .94). The items were (1) “How satisfied are you with the quality of the coffee?” (2) “How satisfied are you with the taste of the coffee?” and (3) “I enjoyed the coffee very much.” We additionally measured involvement to rule out any effects of the regulatory focus prime on involvement in the study. Involvement was measured using three nine point items anchored by “strongly agree/strongly disagree” (α = .94). The items were (1) “I took the task of evaluating the coffee seriously.” (2) “I was motivated to make an accurate evaluation.” and (3) “I took my responsibility of participating in this study seriously.”

4.2. Results

4.2.1. Manipulation checks

As expected, coffee drinkers in the positive consumption experience condition were significantly more satisfied (M = 5.93) than coffee drinkers in the negative experience condition (M = 4.02, F(1, 118) = 42.83, p < .001). There were no differences in involvement between promotion-focused participants (M = 7.32) and prevention-focused participants (M = 7.45; F(1, 118) = .40, p = .53), ruling out involvement as an alternative explanation.

4.2.2. Expectations

Means, standard deviations and correlations are presented in Table 1. A two-way ANOVA revealed a significant main effect of regulatory focus on expectations: promotion-focused individuals had higher expectations of the coffee (M = 6.78) than prevention-focused individuals (M = 6.14, F(1, 116) = 5.65, p = .02).

4.2.3. Satisfaction

The effect of the regulatory focus by consumption experience interaction on satisfaction was significant (F(1, 116) = 10.02, p = .002; Fig. 2). In the positive consumption experience condition, satisfaction with the high-quality coffee was lower for participants in the prevention-focused condition (M = 5.46) than it was for participants in the promotion-focused condition (M = 6.39, F(1, 116) = 5.15, p = .03). In the negative-consumption experience condition, satisfaction with the low-quality (lukewarm with baking soda added) coffee was significantly greater for participants with a prevention focus (M = 4.48) than for participants with a promotion focus (M = 3.57, F(1, 116) = 4.87, p = .03). As in Experiment 1, expectations were not correlated with satisfaction (Table 1). These findings replicate the results of Experiment 1 and, in a different context, demonstrate that regulatory focus affects satisfaction in a manner that is consistent with prevention-focused consumers’ conservative bias.

5. General discussion

The objective of this research was to better understand how regulatory focus influences consumer satisfaction. In Experiment 1, promotion- and prevention-primed participants evaluated photos taken from a camera that they had (hypothetically) purchased. In Experiment 2, promotion- and prevention-primed participants evaluated coffee they actually tasted. In both experiments, we find that satisfaction reported after a positive product experience was lower under promotion than under prevention and that satisfaction reported after a negative product experience was higher under prevention than under promotion. We predicted this pattern of results based on previous studies, which indicated that people with a prevention focus exhibit a conservative bias in judgment and decision making (Crowe & Higgins, 1997; Higgins, 2002). In addition, we argued that this conservative bias should directly influence satisfaction, independent of consumers’ expectations. Experiments 1 and 2 provided strong support for these predictions as the results indicate that the impact of regulatory focus on satisfaction is not related to consumers’ expectations. In demonstrating this direct effect, we contribute to regulatory focus theory and extend our understanding of the drivers of consumer satisfaction.

Interestingly, these results also indicate that regulatory focus can affect consumers’ expectations. It may be that because promotion-oriented consumers pursue ideals and have higher aspirations, they
also have higher expectations for consumption experiences than prevention-focused consumers. Yet, given the strong support in the literature for the disconfirmation of expectations model of satisfaction (e.g., Bolton & Drew, 1991; Oliver, 1980, 1997; Parasuraman et al., 1994), it is likely to surprise some readers that while regulatory focus affects both satisfaction and expectations, those two constructs are not correlated in these data. However, despite its general acceptance, alternatives to the disconfirmation of expectations model have been proposed. For example, Locke (1967, 1969) posited a model of satisfaction that depends on a comparison between what people receive and what they want (versus what they expect). Building on this idea, Westbrook and Reilly (1983) argue that expectations refer to beliefs of what the consumption outcome will be, which may or may not correspond with what is desired or valued in the product. Consequently, expectations and evaluations of a consumption experience will not always correlate. This perspective considers the effect of consumers’ motivations on satisfaction and may be more appropriate when differing goals and value standards are held by consumers — as in the case between those with a prevention versus promotion focus. The current research has examined the impact that regulatory focus has on satisfaction. A fruitful avenue for future research may be to better understand the interrelationships (or lack thereof) between consumers’ regulatory focus, expectations and satisfaction.

Similarly, this article has focused on consumers’ cognitive responses to the consumption experience; however, previous research has indicated that consumers’ decision successes and failures lead to different emotional responses under promotion than under prevention (Higgins, 2002; Higgins, Shah, & Friedman, 1997; Idson, Liberman, & Higgins, 2000). It may be worthwhile for future research to explore the intersection between research on the effects of regulatory focus on emotion and the role of affect in consumer satisfaction (Dubé & Morgan, 1998; Fournier & Mick, 1999; Oliver, 1980, 1997; Westbrook & Oliver, 1991).

From an applied perspective, although consumer satisfaction continues to be an important topic for both academics and practitioners, this research represents a first step towards understanding how consumers’ regulatory focus impacts satisfaction. Failing to recognize the effect of regulatory focus may be a critical oversight, especially for firms operating globally, given that research in cross-cultural consumer psychology has highlighted the importance of interdependent and independent self-views (e.g., Markus & Kitayama, 2003). We know that consumers with a more interdependent self-view (e.g., those from collectivist cultures such as China) tend to be chronically prevention-focused, whereas consumers with a more independent self-view (e.g., those from individualist cultures such as the USA) tend to be chronically promotion-focused (Aaker & Lee, 2001). This research suggests that the principles of regulatory focus theory are especially important in understanding satisfaction for firms engaged in international marketing.

References


The effectiveness of high-frequency direct-response commercials

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ABSTRACT

To optimally schedule commercials for a car repair service, we investigate the impact of direct-response commercials on incoming calls at a national call center by using a unique hourly data set from a Belgium-based company. We address the question of whether advertising effects vary across the hours of the week and thereby provide opportunities for the company to optimize its media plan. We summarize the data with a random-effects hierarchical linear model that treats the hours within the week as a panel of 168 interrelated time series. This model highlights the intraday and intraweek heterogeneity of advertising elasticities.

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1. Introduction

Because of improved data collection methods, scholars have in recent years begun to increasingly measure the effect of direct-response advertising, where individuals are triggered to an immediate call to action. Direct-response advertising is common in interactive media, such as web-based advertising, where effectiveness is measured based on click-through rates, on-site registration, requests for information, and (possibly) actual purchases (see Verhoef, Hoekstra, & Van Aalst, 2000). In our case, we find that direct-response advertising is also important to radio and TV advertising. Direct-response commercials help scholars to measure the impact of advertising more accurately because reactions to commercials can be observed shortly after the commercials are aired, and in most cases, the timing is automatically recorded.

Our context is similar to that of Tellis, Chandy, and Thaivanich (2000). We focus specifically on the effectiveness of advertising with respect to the media plan, the choice of channels, timing, and various creative aspects, such as the length and appeal of the commercials. Other effects of a campaign strategy (e.g., pulsing versus constant advertising and total advertising pressure) are outside the scope of this paper.

High-frequency advertising and sales data, whose observations typically involve minutes or hours, enable scholars to treat advertising as an exogenous variable because media plans are usually set well in advance and because modifications at the hourly level are impossible. Even in the cases of radio and TV, instantaneous adjustments are difficult to imagine because of the administrative delays and the implied need to constantly track responses, though website banners may be automatically modified. Regardless, in the current case, we do not have this situation, which could render the advertising variable endogenous. At the same time, high-frequency data challenge the modeler because intraday and intraweek heterogeneity is likely to exist. Therefore, constant-parameter models are usually not accurate because they neglect the subtle patterns. We address these modeling issues in detail and demonstrate that, in our case, constant-parameter models tend to overlook essential characteristics in the dynamics of the system and, as a result, lead to policy recommendations based on biased results.

We propose a novel methodology to analyze high-frequency advertising and call data by addressing the subtle seasonal cycles while accounting for the moderating variables, such as the spot length, the appeal or message, the time of broadcasting, and the channel. Our treatment of this heterogeneity is the main difference between the current research and that of Tellis et al. (2000).

Various approaches allow for the incorporation of daily or weekly cycles (i.e., high-frequency seasonality) into measurements of advertising...
effectiveness. We consider a linear hierarchical model with two levels.\(^3\) In this so-called linear mixed model (LMM), we assume that the hours within the week are the relevant units of observation. In other words, we treat the high-frequency data as a panel of 168 time series, where the time-dimension comprises 133 weeks. The second level of the LMM links the properties of the hourly data and addresses the daily and weekly cycles in the autoregressive and distributed lag effects. We show that this new model captures our data well and that the results provide useful insights into media plans. Our estimation results reveal limited seasonal heterogeneity with respect to the moderating advertising variables. At the same time, our results indicate that strong seasonal heterogeneity exists in the autoregressive effects. This conclusion contradicts those of the traditional models, which emphasize advertising heterogeneity and ignore the cycles in the autoregressive (AR) terms.

In Section 2, we discuss the relevant advertising literature. In Section 3, we provide the details of our data. In Section 4, we show how an LMM can be useful for analyzing such data, and we present our panel time-series model for the hourly data. In Section 5, we present the estimation results. We discuss model validation in Section 6, and in Section 7, we note some scheduling implications. Finally, we conclude the paper in Section 8.

### 2. Background

If high-frequency data on both sales and advertising are available, one may naturally ask whether the data should be aggregated before being analyzed. High-frequency data can contain more noise, and this noise may be averaged out by aggregation such that in the next stage, the relevant elasticities can be properly estimated.

Two main issues are linked to the benefits of analyzing high-frequency data. The first issue goes back to Clarke (1976), who shows that if the same econometric model is used for different levels of aggregation, then the autoregressive term and the duration of the advertising effect are likely to be overestimated at higher levels of aggregation. Second, Tellis and Fransen (2006) show that scholars need to make explicit assumptions regarding the underlying high-frequency model to make reliable inferences from the aggregate data.

A third issue that supports the use of high-frequency data (if available) is the potential endogeneity of the advertising variable. If the advertising–sales relationship occurs at the hourly level but only annual data are available, then the advertising variable will be endogenous because these plans can be modified within a year. In contrast, if actual hourly data are available, advertising becomes an exogenous variable.

The current study is related to the seminal studies on high-frequency data by Tellis et al. (2000) and Chandy, Tellis, and Thaivanich (2001). Tellis et al. (2000) analyze a data set with characteristics similar to ours and address issues such as the short-term impact of channel choice, the time of day, and the type of commercials. The researchers analyze hourly calls or “referrals” to a 1-800 call center by using a linear autoregressive distributed lag (ADL) model, where the autoregressive term is assumed to be constant throughout the week and the day. They report an average carryover effect of approximately 8 h, with a delayed peak impact depending on the time of day. Their model allows for the effects of advertising wear-in and wear-out (see also Naik, Mantrala, & Sawyer, 1998). Tellis, Chandy, and Thaivanich find that high repetition leads to advertising wear-out but that spacing between advertising bursts is beneficial.

The key difference between our analysis and that of Tellis et al. (2000) is that we do not assume the model parameters to be constant across the hours within a week. In contrast to a constant-parameter ADL model, our model treats each hour separately and, thus, analyzes a panel of 168 hourly time series (within a week). In this sense, our model allows for more (seasonal) heterogeneity than the constant-parameter ADL model.

Another study using high-frequency measurements is that of Verhoef et al. (2000), who propose an experimental design on the effectiveness of direct-response commercials. They test two campaigns on two local stations for two different services. The impact measure is restricted to incoming calls in the next 15 min and does not consider carryover or dynamic effects. In contrast, our model follows Tellis et al. (2000) and explicitly focuses on carryover effects. Bass, Bruce, Majumdar, and Murti (2007) propose a Bayesian dynamic linear model to evaluate the dynamic effects of different advertising themes. More specific details on their study appear in Table 1, where we compare our study to the three aforementioned studies.

### 3. Data

#### 3.1. Company and data background

We derive our data from a car repair service located in Belgium. The company is part of a multinational firm that offers similar services worldwide. The service consists of either direct intervention in emergency situations or preventive actions. The advertiser has been

<table>
<thead>
<tr>
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<th>Type of effect</th>
<th>Advertising model</th>
<th>Order of AR process</th>
<th>Order of DL process</th>
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<td>Month</td>
<td>Month</td>
<td>Strong intraday</td>
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\(^3\) Similar to Naik et al. (1998), we can also utilize continuous time models, but doing so would allow for too much flexibility in the sense that all of the parameters can vary freely. In fact, as our estimation results will show, most of the variation in the parameters seems to be seasonal in nature. Thus, we decide to consider a model that explicitly highlights this variation.
broadcasting direct-response radio and TV commercials for many years. It primarily advertises on national radio and TV, and its commercials are broadcast through all available national radio and TV stations. The company spreads its spots throughout the week at irregularly spaced intervals, and most of the daytime hours are used for radio commercials. The company uses TV advertisements less intensively. There is no systematic pattern in the timing of these spots. The company makes its broadcasting plans months in advance and negotiates its plans with the media. Traditional car repair companies can provide similar services, but this advertiser is by far the market leader for this specialized service. Because this company is the only supplier that uses national advertising, its share of voice is 100%. The advertising data are complete in that the company employs no other communication channels (e.g., print advertising and outdoor advertising). These characteristics are essential for our purposes because they allow us to make a differentiated assessment of the advertising impact by channel and by time slot with little contamination from other, possibly unobserved, effects. The advertising policy covers a large spread over the available channels and time slots. Additionally, it provides an exceptional opportunity to produce detailed insights into the dynamic effects of advertising.

Because consumers can suffer a car breakdown that requires immediate intervention, the company has organized a mobile intervention service conducted by a national call center that operates 24/7 on a 24/7 basis because an important part of its activities pertains to direct interventions for acute situations. Calls arrive at the call center either directly through the 0800 number or through the regional service centers, which then subsequently transmit the calls to the call center. The calls in the latter case are less influenced by advertising because these numbers are not advertised. Approximately 30% of the calls are classified as “not relevant,” which indicates that they are not related to the service. Some of the relevant calls result in appointments and eventually generate actual repair jobs. These calls constitute our preferred unit of analysis. However, because the registration of relevant calls has experienced changes within our observation period and because such calls are more directly linked to the commercials, we focus on the 0800 calls and set these calls as the appropriate dependent variable. The correlation between the total number of incoming 0800 calls and relevant calls is 0.96. The data cover the period from May 13, 2003 to December 1, 2005.

3.2. The calls data

By analyzing the calls data at the hourly interval, we generate 22,416 observations. When we treat these data as a single time series, the Dickey–Fuller test shows that the series are stationary (p-value = .00005). Thus, there is no unit root in the log(0800 calls + 1) series. When we apply the Dickey–Fuller test to each of the 168 series, we find the same result. All of the series are stationary. The absence of a unit root indicates that advertising may have an immediate effect on the incoming 0800 calls that persist over some time.

4 A logarithmic model stabilizes the residual variance. We add 1 before taking the natural logarithms because the number of 0800 calls is sometimes zero. From a conceptual standpoint, we can consider the number of calls to be count data, where the zeros could be treated as they are in a Tobit model. However, for most hours, the number of zeros is limited. Additionally, a model containing some Tobit equations and some log-linear equations would complicate our analysis and inference process. Thus, we decide to treat the zeros as regular observations.
but not permanently (for a discussion of unit roots in sales and advertising data, see Dekimpe & Hanssens, 1995). In addition, we do not need to analyze the growth rates and can focus on the levels of the data instead. The data interval of 1 h coincides with the single-exposure time interval, as Tellis and Franses (2006) recommend, with the exception of a few occasions in which two spots may have been scheduled during the same hour on a particular channel. In addition, using the hour as the observational unit fits nicely with the media plan.

Fig. 2a shows the evolution of calls over the sample period. Fig. 2b shows the distribution of 0800 calls by the hour of the week. This distribution shows a seasonal cycle that bears some similarity to the distribution observed by Tellis et al. (2000).

3.3. Media plans and advertising data

Table 2 provides a summary of the radio and TV commercials in the observation period. The company records 5172 radio commercials, which are spread over six radio stations and are broadcasted between 6 a.m. and 9 p.m. Most of the radio spots are 20 s long, and more than half of these spots are aired through one radio channel (Radio 2).

The company uses five ad appeals. Because the spot length and theme are closely related, identifying their possible effects is sometimes difficult. For example, the company has used Theme 4 (a price promotion) 165 times, but this theme always has a spot length of 15 s. The company has used the main theme, which promotes preventive maintenance, 2389 times across 5 different lengths, but in 2112 of these instances, the company used this theme in a 20-second radio spot. Tables 3 and 4 provide summaries of the scheduling by the hour of the day and the by day of the week, respectively. These summaries show that most of the commercials are aired at 7 a.m. There are 20% fewer commercials on Fridays compared with other weekdays. Weekend radio commercials are relatively rare, with only 73 on Saturdays and 28 on Sundays.

Table 2

<table>
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<th>15</th>
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<td>130</td>
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<td>30</td>
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<td>0</td>
<td>9</td>
<td>180</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>Radio 5</td>
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<td>0</td>
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<td>280</td>
<td>10</td>
<td>9</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>108</td>
<td></td>
</tr>
<tr>
<td>TV 2</td>
<td>29</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>66</td>
<td></td>
</tr>
<tr>
<td>TV 3</td>
<td>33</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Total</td>
<td>30</td>
<td>350</td>
<td>393</td>
<td>2603</td>
<td>189</td>
<td>1754</td>
<td>40</td>
<td>67</td>
<td>5426</td>
<td></td>
</tr>
</tbody>
</table>
We measure the advertising intensity of a commercial by using GRPs (Tellis, 2004). In the current study, the GRPs are related to the 25–55 age group, which is considered the relevant target segment for the product. For four of the six radio channels, we obtain the GRPs by using a “portable people meter,” which registers a radio data signal emitted at the beginning of the commercial if a person is exposed to the commercial. By using this signal, we generate GRPs at the level of the individual commercial. For the two other radio channels, we obtain GRPs from a diary panel, which results in quarterly waves with constant GRPs during a particular wave for a given channel and time of week. For TV, we directly register the advertising exposure from the TV set of the participants in the panel.

The number of TV commercials is small (i.e., only 254 spots) and are mainly concentrated in a single wave. Because of this small sample size, the reliability of the estimated impact of TV spots is limited. TV spots come in two lengths (i.e., 15 and 30 s) and use essentially the same appeal.

4. Model

To meet the specific features of the data, our methodology draws on so-called linear hierarchical models (see Verbeke & Molenberghs, 2000). We formulate our linear hierarchical models as follows:

\[ Y_{ht} = Z_{ht}(K_{ht}eta + b_{ht}) + \epsilon_{ht}, \]

where \( Y_{ht} \) is the Level 1 dependent variable; subscript \( h \) refers to a subject, which in our case is the hour of the week; and \( t \) is the week. The term \( Z_{ht} \) in Eq. (1) is a matrix of the hour-specific explanatory variables associated with the vector of coefficients \( b_{ht} \). The model also contains a set of Level 2 equations for the \( b_{ht} \) parameters. We model these equations as functions of a subject-specific matrix of exogenous variables \( K_{ht} \) and a random effect (or error term) \( b_{ht} \), which is associated with each of the subject-related parameter vectors.

Previous marketing researchers have used linear hierarchical models (e.g., Pauwels, Srinivasan, & Franses, 2007), but the subjects in these studies are usually brands or individuals. In our study, the subjects are the hours within a week. The estimation method used in marketing applications primarily consists of a two-step process. First, the researchers estimate the Level 1 parameters for each subject. Second, based on the resulting estimates, the researchers obtain the Level 2 parameters (for an application, see Pauwels et al., 2007). Scholars have also applied hierarchical Bayes methods when jointly estimating the parameters for both levels (see Fok, Horvath, Paap, & Franses, 2006). However, this approach is inapplicable for our problem.

Estimating the hierarchical models in a two-step approach has certain limitations, as discussed by Verbeke and Molenberghs (2000), who recommend a full-information approach by substituting the Level 2 equations into Level 1 and then using the resulting LMM in Eq. (2).

\[ Y_{ht} = Z_{ht}(K_{ht}eta + b_{ht}) + \epsilon_{ht}, \]

where \( X_{ht} = Z_{ht}K_{ht} \) is a matrix of the explanatory variables.

We can estimate LMMs such as Eq. (2) by using maximum likelihood or Bayesian methods. The latter approach has gained in popularity in the last decade. Zhang, McArdle, Wang, and Hamagami (2005) provide an example in which the two estimation approaches lead to similar results, particularly when the sample size is large. Because we also have a large dataset (133 weeks), we rely on SAS Proc Mixed based on a maximum likelihood estimation approach to perform our estimation because this method is more convenient to use with than the Bayesian approach.

4.1. Level 1 specification

We want to estimate the impact of direct-response commercials on incoming calls at the call center and to examine the mediating
roles of channels, the time of broadcasting, theme, and the spot length of the commercials. We perform this estimation with our LMM, which allows the coefficients to vary by the hour of the week. The Level 1 equations contain 1- and 24-hour lags of the calls. We test higher-order lags but find them to be insignificant. For advertising, we include the GRPs in the current hour and in the one-hour-lagged value. This lag exists because many spots are placed during the final minutes of the hours such that the consumers can react only in the next hour. Including higher-order lags is not productive because prior experiments have shown that doing so results in erratic signs and low significance levels. For TV spots, the total GRPs for a given day extend to the next day.

Fig. 2a and b show the intraday, weekly, and yearly cycles in the call pattern. A weak downward trend exists as well. The yearly cycle may be approximated well by a goniometric wave. We enter this wave into the model as a sine and a cosine function of time with a one-year periodicity. Finally, holidays, which amount to approximately 15 days per year, have a pronounced impact on the days preceding the holiday, the day itself, and the day following the holiday. Thus, we include dummies for the holiday, lead holiday, and lagged holiday. For the holidays themselves, we recode the hours as Sunday hours based on a visual inspection of the call levels.5

The typical day/week pattern leads us to adopt an LMM in which the measurement units are the hours in the week and run from 1 to 24.

Because we perform this recoding after performing other data manipulations, especially the computation of lagged values, the recoding does not interfere with the AR and DL effects.

---

5 Because we perform this recoding after performing other data manipulations, especially the computation of lagged values, the recoding does not interfere with the AR and DL effects.
Table 5  
Structural coefficients (standard errors in parentheses).6

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Const</th>
<th>Daily sine</th>
<th>Daily cosine</th>
<th>TV channel</th>
<th>Length</th>
<th>Theme</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>AR (1)</td>
<td></td>
<td></td>
<td></td>
<td>Mon</td>
<td>Tue</td>
<td>Wed</td>
</tr>
<tr>
<td>λ1</td>
<td>0.25 (0.01)</td>
<td>λ1</td>
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</tr>
<tr>
<td>θ1</td>
<td>1.04 (0.02)</td>
<td>-0.56 (0.02)</td>
<td>-0.60 (0.02)</td>
<td>-0.06 (0.02)</td>
<td>-0.06 (0.02)</td>
<td>-0.04 (0.02)</td>
</tr>
</tbody>
</table>

6: ns: nonsignificant variables with |t|<1 are eliminated from the estimation. The following are used as benchmark categories where needed: daily dummy variable: Sunday; radio: Channel 6; radio spot length: 20 s; radio spot theme: Campaign 5; TV: Channel 3; TV spot length: 15 s.

168. Because there are 133 weeks of data, the panel is composed of 168 units with 133 weekly observations.

We define the Level-1 specification of our LMM as follows:

\[ Y_{h,t} = \theta_{h,t} + \lambda_{1,h}Y_{h-1,t} + \lambda_{2,h}Y_{h-2,t} + \phi_{1,t}R_{h-1,t} + \phi_{2,t}R_{h-2,t} + \gamma_{TV}TV_{h,t} + \gamma_{d,t}DTV_{d-1,t} + \gamma_{s,h,t}S_{h,t} + \gamma_{c,h,t}C_{h,t} + \epsilon_{h,t} \]

where \( h \) is the hour in the week (1–168), and \( t \) is the index for the week (1–133). The parameters contain an index \( h \) if they vary by the hour of the week and an index \( (h,t) \) if the variation across hours is caused by, for example, the GRPs of specific channels. The index \( d \) for DTV refers to the total TV GRPs broadcasted during a day. This value is then included for all of the hours of the next day. Coefficients without time-related subscripts are homogeneous across hours, as is the case for the immediate (current) impact of the TV spots \( (\gamma_{TV}) \) and for the trend and the holiday effects. The superscript \( c \) in the parameters denotes the current-hour effects, \( l \) is the one-hour-lagged effects, and \( d \) indicates the next-day effects.

We defined the variables in Eq. (3) as follows:

\[ Y_{h,t} = \log(Calls_{h,t} + 1) \]

is the dependent variable, where the autoregressive terms are included at hourly lag 1 and hourly lag 24.

\[ R_{h,t} = \log(Radio\ GRP_{h,t} + 1) \]

refers to the GRPs of radio advertising, which is included in the current and previous hours.

\[ TV_{h,t} = \log(TV\ GRP_{h,t} + 1) \]

is the GRPs of TV advertising, which is included in the current and previous hours.

\[ DTV_{d,t} = \log(Calls_{h,t} + 1) \]

is the total amount of TV GRPs during a day, which is included in all hours of the subsequent day.

\[ B_{h,t} \]

is a dummy variable for bank holidays.

\[ S_{h,t} = \sin(\frac{h\pi}{2}) \]

and \( C_{h,t} = \cos(\frac{h\pi}{2}) \) are harmonic regressors covering the yearly cycle.

\[ Tr_{h} \]

is a trend defined as \( t/52 \), where \( t \) is 1, 2... 133.

Before taking the logs, we add 1 to the data on calls and GRP to account for the zero values. The calls during night hours are particularly low and sometimes zero. The incidence of hours with zero calls is substantial during the night hours (i.e., between 0 and 5 am) and reaches a maximum of 86% at 4 am on the weekdays (66% on the weekends). However, these hours are of limited interest because there is no advertising or lagged effects at these hours. Therefore,
there is no need to utilize alternative modeling techniques, such as a Tobit or count data regression.

The television commercials are mainly concentrated in the evening or night hours. Therefore, the intraday impact of the TV spots is small. Because the benchmark level of the calls is low, even high-value parameters will still translate into a small effect. However, we might expect substantial next-day effects for the TV spots but not the radio spots, for which lesser next-day effects may be found. Rather than apply a simple 24-hour lag, we include the next-day effects for the TV spots as the total amount of the GRPs from the previous day (DTV_{a−1,i}) for all of the channels combined. We include the effects for all hours of the next day as well.

4.2. Level 2 specification

A visual inspection of the patterns of the Level 1 equations sometimes suggests that intraday cycles exist for some coefficients. This finding can guide the Level 2 specification. We clearly observe such cyclic behavior for the autoregressive effects, but no such effect is evident for the advertising coefficients (see Fig. 3). For the advertising coefficients, we include the moderators of advertising effectiveness (i.e., the time of broadcasting, the channel used, the spot length, and the advertising theme used) as the sources of heterogeneity. Timing and channel choice are more directly related to the media scheduling, whereas spot length and theme are related to the campaigns and to the creative aspects rather than to the media plans. We expect the themes to have small effects because these themes are not substantially different across the commercials.

For the Level 2 equations, we distinguish between the structural effects (i.e., systematic time-varying influences on the coefficients) and the random effects. Both sources induce heterogeneous or time-dependent effects. Fitting complete Level 2 (i.e., fixed and random effects) equations into all of the parameters such that all of the equations have error terms would lead to a tremendous inflation in the number of parameters. We delete all of the regressors when their associated t-values are smaller than 1 in absolute value. In the Level 2 equations, we drop the error terms when one of two conditions is fulfilled: (a) the variance–covariance matrix of the random effects is no longer positive definite or (b) the estimation process no longer converges. We assume that the holiday variables are homogeneous.

We include the Level 2 random effects in the equations for the yearly cycle, for the autoregressive terms, and for the effects of radio advertising. For TV advertising, there are not enough active hours and active weeks available to model the effects. Therefore, the random effects of TV advertising cannot be estimated. Because spot lengths and themes for radio are closely linked, we cannot include all of the lengths and themes.

Franses and Paap (2011) suggest the use of goniometric time-varying coefficients to obtain a parsimonious model of seasonality in the Level 2 equations. We find that this method works fine for the intercept and the lagged log of the number of calls (Eqs. (4) and (5) below), which we model as goniometric cycles with a one-day periodicity. However, a goniometric wave is not always applicable. For example, for the yearly cycle, a constant structural effect with a random component seems to be sufficient. The goniometric day cycle has different intercepts across the weekdays, and the first-order autoregressive (AR(1)) coefficient shows different amplitudes for each weekday. Fig. 3 compares the Level 1 coefficients with the final estimates. The error terms in the Level 2 equations allow the LMM estimates to closely mimic the directly obtained Level 1 coefficients.

On the basis of the preceding considerations, we now provide the details of the Level 2 equations. The model for the intercept (θ_{h,t}) contains a goniometric day cycle, with a day-of-week-specific dummy D_{i} (where i = 1 indicates Monday) that allows for shifts in the intercept for different weekdays. We define the hour of the day as hh, which ranges from 1 to 24. We first specify the following:

\[ θ_{h,t} = θ_0 + θ_1 \sin \left(\frac{2\pi h d}{24}\right) + θ_2 \cos \left(\frac{2\pi h d}{24}\right) + \sum_{i=1}^{6} θ_i D_{i,t}. \] (4)

The first-order autoregressive coefficients (λ_{1,h,t}) obey a wave with a 12-hour periodicity. The symbol for the hour is now hh and ranges from 1 to 12. Thus, we have:

\[ λ_{1,h,t} = λ_{1}^{1} + \sum_{i=1}^{7} λ_{1,i} D_{i} \sin \left(\frac{2\pi h d}{12}\right) + \sum_{i=1}^{7} λ_{1,i} D_{i} \cos \left(\frac{2\pi h d}{12}\right) + b_{1,h,t}. \] (5)

where we multiply the sine and cosine terms with the day-of-the-week dummies. The second-order AR (λ_{2,h,t}) parameters do not
show a systematic pattern. Therefore, we model them as homogeneous, with the exception of an error term:

\[ \lambda_{2} h, t = \lambda_{2} + b_{2, h, t}. \]  

(6)

We define the current-hour radio advertising effects (\( \phi_{h, t} \)) as:

\[ \phi_{h, t} = \sum_{i=1}^{\text{channels}} \phi_{i}^{h, c} FC_{i, h, t} + \sum_{l=1}^{\text{lengths}} \phi_{l}^{h, l} FL_{t, h, t} + \sum_{t=1}^{\text{themes}} \phi_{t}^{h, t} FT_{t, h, t} + b_{3, h, t} \]  

(7)

where \( FC_{i, h, t} = \frac{\sum_{k=0}^{R_{i, h, t}} \text{GRP}_{k}}{\sum_{k=0}^{R_{i, h, t}}} \) is the fraction of radio GRPs obtained from channel \( i \). Similarly, \( FL_{t, h, t} \) and \( FT_{t, h, t} \) are the fractions pertaining to a specific length and a specific theme.

Similarly, we define the distributed lag term for radio advertising (\( \phi_{h, t} \)) as:

\[ \phi_{h, t} = \phi_{0} + \sum_{i=1}^{\text{channels}} \phi_{i}^{h, c} FC_{i, h-1, t} + \sum_{t=1}^{\text{themes}} \phi_{t}^{h, t} FT_{t, h-1, t}. \]  

(8)

An error term might seem plausible here, but we do not include it because the relevant variance–covariance matrix becomes nonpositive definite. We drop the spot length effect because it is not significant.

For TV advertising, only the spot length and channel are relevant, and the themes are not available. We find that the current TV effect (\( \gamma' \)) has no significant moderating effects. Therefore, we model this effect only as a fixed effect. We model the one-hour-lagged TV effect (\( \gamma_{h, t} \)) as:

\[ \gamma_{h, t} = \gamma_{0} + \sum_{i=1}^{\text{channels}} \gamma_{i}^{d} FTC_{i, h-1, t} + \gamma_{t}^{d} FTVL_{d, h-1, t} \]  

(9)

where \( FTC_{i, h-1, t} \) are the fractions of channel GRPs, and \( FTVL_{d, h-1, t} \) is the fraction of spots with length 30.

The next-day TV effect (\( \gamma_{h, t} \)) accounts for the fractions of channel and length GRPs and the hour of broadcasting through the dummy variables for the hour (\( H_{i, t} \)), as shown by the following:

\[ \gamma_{h, t}^{d} = \gamma_{0} + \sum_{i=1}^{\text{channels}} \gamma_{i}^{d} FTC_{i, d, h-1, t} + \sum_{i=1}^{\text{themes}} \gamma_{i}^{d} D_{d, t} + \sum_{i=1}^{\text{themes}} \gamma_{i}^{d} Hi_{t} \]  

(10)

We model the seasonality effects, which are specified in Eqs. (11) and (12), as homogeneous combined with random effects, as shown by the following:

\[ \delta_{h, t}^{c} = \delta_{0}^{c} + b_{4, h, t} \]  

(11)

\[ \delta_{h, t}^{d} = \delta_{0}^{d} + b_{5, h, t}. \]  

(12)

To recap this section, we utilize an LMM for hourly data, where the Level 2 equations can yield useful information on the intraday variation with respect to the advertising effects. We considered various alternative specifications of the model. The process leading to the final specification is partially data driven. The features of our decision process are as follows:

- Some features are mainly data-based. Examples of such features include the order of the AR terms and the DL terms and the presence of a trend. In addition, we consider a two-hour lag to be a realistic choice because of the broadcasting schedules and the assumption that direct effects are relatively short-lived (see Verhoef et al., 2000).
- Some features are linked to the hypothesis of interest (i.e., the moderating advertising effects are heterogeneous). However, if these effects are not significant, we believe that pruning the model is safer. Thus, the parsimony achieved avoids considering several, usually small, and always insignificant effects.
- The random effects model is an expensive model in terms of the number of parameters, not least of which because of the large number of random effects that may also be included. If too many random effects are included, the associated variance–covariance matrix may no longer be positive definite. This problem is well known, and previous scholars have suggested various approaches to address it. It is similar to the multicollinearity issue, where redundant variables could be eliminated. We follow an analogous procedure. That is, we avoid adding random effects for less important variables (e.g., holiday effects), and we eliminate the random effects diagnosed as causing estimation problems. The analogy with multicollinearity issues is also reflected in the way that random effects act to some extent as “subject-” or hour-related dummy variables in forecasting. Thus, at one point, adding more random effects might be harmful.

5. Estimation results

A key finding of our study is the daily cycle found for the one-hour-lagged and one-day-lagged effects. The one-hour-lagged cycle is highly significant, with a peak of 1.08 on Monday at 8 a.m. and a low of −.04 on Wednesday at 5 a.m. The structural part of this AR(1) parameter varies between −.04 on Sunday at 12 p.m. and .55 on Monday at 12 a.m. The one-day-lagged (AR(24)) structural effect is fixed (.10), but when it includes the random effects in the error term, the structural effect reaches a peak of .57 on Wednesday at 8 a.m. and a minimum of −.20 on Wednesday at 5 a.m. As a result, the total autoregressive variation ranges from 1.51 (Monday at 8 a.m.) to −1.17 (Monday at 5 a.m.). The variation exceeds 1 for 2 of the 168 h (both on Monday morning) and is negative for eight hours.

Table 5 summarizes the structural coefficients. For the equations containing random effects, we report the standard deviation of the random effects over the time of the week in the last column. Most of the fixed effects are significant. For Channels 2, 4, and 5, we find a significantly higher-than-average effectiveness. Theme 2 is also significantly more effective than average. Themes 2 and 3 are significant but negative in the lagged radio advertising equation. The impact of TV in the current hour is large and significant, though none of the moderating effects are significant. The lagged TV effects are high for the 30-second spot length and for Channels 1 and 2. The next-day effects of TV advertising vary by the hour of the day and the day of the week, with Mondays appearing to be the least effective. The hour effects are also mostly negative, and the 30-second spot length has a significant, negative effect. However, note that an analysis of the partial effects may be misleading because a spot is always a combination of timing, theme, length, and channel. In addition, the positive and negative next-day effects relate to different base levels and may, to some extent, offset each other. In Section 8, we utilize simulations for the media planning process to derive insights from our model.

The hour-of-week random effects for the yearly sine (\( b_{a, h, t} \)) and cosine (\( b_{s, h, t} \)) waves are significant at the 5% level for 20 and 17 h out of the total of 168 h, respectively. For current-hour radio advertising (\( b_{a, h, t} \)), 32 out of 85 active hours are significant. The random effects for the current-hour radio coefficients are significant and positive at their peak (7 a.m.) for all weekdays. We find a consistent cyclical pattern consisting of mostly positive effects in the morning hours and negative effects later in the day. This pattern applies to the AR(1) and AR(24) parameters and, in particular, to the current-hour radio advertising. In summary, our model seems to capture several detailed features of the data. Table 6 shows the standard deviation of the random effects across the hours of the week.
Managers are often interested in the long-term (or total) impact of advertising (Dekimpe & Hanssens, 1995). We compute the total impact based on the average GRPs observed during the sample period by the time slot and by the channel. In linear ADL models, one obtains the total impact from the standard formula \( \sum \phi k (1 - \sum \lambda k) \). Note that if the data are transformed by using natural logarithms, as in our case, this formula does not apply. Therefore, we obtain the total impact by simulating the process at the middle of the sample and by comparing the results of this process with the baseline forecasts without advertising.

Channel 2 has the highest impact per spot. The pattern of the impact over the week is similar for all of the channels because the GRP cycles are highly similar. Note that the effect of radio advertising decreases gradually during the week (see Fig. 3b).

The other radio channels score 99% (Channel 6), 59% (Channel 4), 39% (Channel 5), 37% (Channel 1), and 8% (Channel 3). This last channel is the pop station, which aims at a different type of audience.

The total impact per TV spot reaches a peak of 58 calls on Monday at 10 p.m. and drops to a minimum of 4 calls on Thursday at 3 p.m. The impact of radio advertising reaches a high of 78 calls per spot on Monday at 7 a.m. and a low of 17 calls per spot on Friday at 6 p.m.

Fig. 3b provides no evidence of a wear-out effect during the week of a campaign. However, as we show in the section on the implications of media scheduling, the effectiveness of advertising, as measured by total impact, is much higher early in the week.

What would we have learned from the data if we had used a constant-parameter ADL model? Fig. 4 compares the total impact per spot resulting from our LMM and a constant-parameter ADL model with autoregressive lags at 1 and 24 h. The horizontal axis of the graph represents an hour within the week arranged in decreasing order of the total impact per spot, which was generated by the LMM.

The results clearly show that the magnitudes and hours of the peak impact are markedly different across the models. In particular, the peak impact from the LMM is much sharper. The secondary y-axis of the graph (right-hand side) refers to the incremental calls per euro spent, which we obtained from the LMM. The incremental calls per euro spent are highly consistent with the LMM’s ranking of the impact per spot. The variations in the total impact are caused by the interaction among three factors: autoregressive effects, which peak at 7 a.m.; the intraday calls cycle, which peak at 9 a.m.; and GRP variations, which are less volatile but are highest at 10 a.m.

These three drivers follow a similar pattern over the week. Thus, the LMM clearly allows for more refined analysis than the constant-parameter ADL.

The last driver of the calls is the impact of advertising per GRP, which we find to be much less heterogeneous across the hours than the other effects. This finding leads to the conclusion that the highest-impact time slots are the hours with high-value autoregressive parameters, GRPs, and baseline levels. The advertisements broadcasted at 7 a.m. generate more calls per euro spent than the advertisements broadcasted at other hours. The daily pattern of the impact per euro spent is highly similar across the days.

6. Validation

A possible threat to the model validity is multicollinearity. Multicollinearity prevents advertising themes 1 and 3 from being analyzed by the model because the effect is confounded with spot length effects. Multicollinearity might also be induced by the autoregressive and distributed lag terms. However, the two highest mean-centered variance inflation factors (VIFs) are 18 and 19 and are related to the current and lagged GRP terms, respectively. All of the other VIFs are smaller than 5. Thus, although increasing the order of the distributed lag terms for the radio GRP might considerably increase multicollinearity, it is not a serious problem in our final specification.

All of the coefficients in our LMM are acceptable in size, except perhaps for the parameters pertaining to Monday at 7 a.m., for which we obtain an exceptionally (and unexpectedly) high impact. The results also show that the effects of TV spots are strong, but as we noted previously, this finding is based on limited evidence.

Furthermore, the LMM produces an impressive fit at the micro level. The in-sample root mean square error (RMSE) for the logarithm of the calls is .413. The constant-parameter ADL model used in the earlier comparison of advertising effectiveness yields an RMSE of .426. Thus, the in-sample fit of the LMM is better than the constant-parameter ADL model. The RMSE for the out-of-sample forecasts, where the models are fit to the first 15,120 observations and are validated for the remaining 7,296, is .425 for the LMM and .430 for the ADL model. This last result is striking because models with more parameters are commonly found to yield worse forecasts (Ebersbach, Lehner, Resing, & Wilkening, 2006), but here the opposite result occurred. Although the LMM is a powerful vehicle when testing for the heterogeneity of advertising effects over channels, time slots, and spot characteristics, its out-of-sample forecast accuracy is not significantly different from the out-of-sample forecast of the traditional ADL model.

A small amount of autocorrelation appears to exist in the residuals of the model. The white noise test statistic (Bartlett’s Kolmogorov-Smirnov Statistic) is .025, with a p-value smaller than .0001. Closer inspection reveals that the maximum value of the autocorrelation in the residuals is only .034. This small and economically insignificant value allows us to conclude that we can abstain from modifying the model by including more lags.

7. Implications for media planning

If no additional constraints exist (e.g., if no channel bundling exists), one can compute an optimal schedule by using a greedy algorithm (see Weingartner, 1974). We somewhat simplify our procedure by assuming that the cost per GRP is the same across the channels and time slots. However, if this assumption is incorrect, then the effectiveness per GRP must be replaced by the effectiveness per euro spent. The process consists of two steps: a simulation step followed by an optimization step.

7.1. Simulation step

Step 1: Compute the benchmark call levels for a reference week. We take the average calls over the entire sample as the starting point. Note that in real-life media planning, the calls of the last week would be used instead. The reference week serves to define the lagged call levels that span weeks because of the autoregressive effects. These effects pertain only to the one-day lag of the calls in our case.

Step 2: Compute the benchmark call levels for the next week if no advertising exists.

Step 3: Iterate over all of the channels and relevant hours and define the media plan as generating 1 GRP for that slot. With this media plan, we compute the week-ahead forecasts for the entire week.

Step 4: Compute the difference between the total number of calls for the week and the total number of the benchmark calls. The result is the impact per GRP for each relevant slot.

The entire process can be repeated by using the average GRPs observed over the sample period for a specific spot. Doing so will lead to estimates of the total impact per spot.
### 7.2. Optimization step

The results yield a table for the time slots and the channels of total impact per GRP, which is converted into an ordered list. This list enables us to assess the optimality of the existing media plans or to design an optimal media plan. Each time slot and channel can be viewed as an investment opportunity. Because the model assumes that no interactions exist between the hours or channels, the optimal rule consists of picking the slots and channel combinations in decreasing order of impact/GRP. Weingartner (1974) discusses how this approach fits into an integer linear programming model, which would allow for additional constraints, such as possible bundling restrictions among channels.

By picking the slots in decreasing effectiveness per GRP until the desired GRP is achieved, the company can realize the maximum total impact of the target level of GRPs. An alternative solution might be to advertise until the cost of the last spot scheduled is equal to the revenue obtained from the calls generated. We illustrate this process in Table 7 for Channels 1 and 2, with a cutoff of 3 calls per GRP. This process would generate a total of 41 GRPs, which would result in 276 extra calls.

Assuming that the company aims for approximately 300 GRPs or a minimum response of 3 calls per GRP (whichever comes first), we provide an optimal schedule for all six radio channels in Table 8. This schedule achieves over 284 GRPs, which results in 891 incremental calls. The time slots are given in decreasing order of impact for a given combination of day and channel. The slots in parentheses were not used in the sample, but the model ranks them as having a relatively good potential impact. No weekend spots are retained in the optimal schedule. Based on the results, we can see a clear pattern that favors a few channels and also emphasizes advertising on Mondays, with the effectiveness decreasing as the week progresses. In the LMM, 241 GRPs scheduled for the most effective 131 slots generate 777 extra calls with an average impact/GRP of 6.65. Compared with the ADL model, 240 GRPs scheduled for the most effective 131 slots generate 177 extra calls with an average impact/GRP of 1.4. In fact, the ADL model yields impact estimates that are below 3 calls/GRP for all of the slots (see the right-hand panel in Table 7 (Total Impact/GRP)).

<table>
<thead>
<tr>
<th>Table 8</th>
<th>Optimal media plan radio obtained from LMM².</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day</td>
<td>Time slots (hour of day)</td>
</tr>
<tr>
<td>Channel</td>
<td>Total slots (hour of day)</td>
</tr>
<tr>
<td></td>
<td>Monday</td>
</tr>
<tr>
<td>1</td>
<td>7, 8, 6, 9</td>
</tr>
<tr>
<td>2</td>
<td>7, 8, 6, 9, (5), 10</td>
</tr>
<tr>
<td>3</td>
<td>7, 8, 6, (5), 9, (7), 8</td>
</tr>
<tr>
<td>4</td>
<td>7, 8, (6), 9, 10, (5), 11, (14), 12, 13, (15), 12, (13), (6)</td>
</tr>
<tr>
<td>5</td>
<td>7, 8, (6), 9, (10), (5), 11, (14), 12, 13, 15, (16), (15), (6), 15</td>
</tr>
<tr>
<td>6</td>
<td>7, 8, 6, 9, (5)</td>
</tr>
<tr>
<td></td>
<td>Total</td>
</tr>
</tbody>
</table>

### 8. Conclusions

Our detailed analysis of a unique database uses a new LMM, which treats the hours within weeks as panel subjects, to provide new insights into the dynamics of advertising effects. The results show that the LMM is a powerful tool, notwithstanding the higher complexity and the delicate balance between the specification and estimation opportunities. In terms of predictive validity, the LMM is even better than the restrictive constant-parameter ADL model, but the normative implications are even more different.

We aimed to examine whether the timing, channel, spot length, and theme of a commercial affect the impact of advertising. We found that timing is the key driver. There are two reasons for this finding. First, advertising works best at peak demand hours. This effect is amplified by a second, less obvious reason: at peak hours, the autoregressive parameters leverage the impact to an even higher value. This carryover effect decreases dramatically after the peak hours. The effectiveness per GRP varies in decreasing order across the channels, themes, and spot lengths, but the total impact of these characteristics is relatively small.

The combined structural and random effects of the model strongly affect the variation in advertising effectiveness across the hours in the week. The same would not have been true under a constant-parameter ADL model. The intraday pattern of the autoregressive effects, the fluctuations of GRPs over each day, and the intraday calls pattern seem to reinforce one another. Together, they cause the impact at peak hours relative to the impact at off-peak hours to be much more pronounced than the competing models suggest.

From a modeling perspective, the intraday heterogeneity lends strong support to the use of LMMs for high-frequency marketing data. Our conclusion is that the intraday heterogeneity of the lag
structure may be an important aspect that has been overlooked in the literature. This heterogeneity may affect the conclusions about aggregation put forward in the prior studies.

Our study has implications for practical media planning. The results suggest that radio spots should be concentrated at the morning peak of 7 a.m. and simultaneously use all of the effective channels. A second drawback is the limited diversity of the advertising themes examined in this study. More substantial variation in themes might lead to larger differences in advertising effectiveness. The limited number of TV spots, which caused the reliability of their impact estimates to decline, also creates difficulties for the level-2 specifications. Another limitation of our study might be that it does not account for the effectiveness of the advertisements on the respondents’ attitudes and memories. Based on our interactions with the management, we know that their consumer research finds consistently high levels of brand awareness. However, assessments of the customers’ attitudes toward the ads, which may help clarify the differences in effectiveness, are not available. Finally, we did not integrate a profitability analysis of the media scheduling into our study, although we are aware that the company has followed up on the return-on-investment implications of our study.

To validate our approach in other contexts, we must satisfy other conditions. The most important of these conditions is that the study must be conducted within the context of a direct-response model. The second condition demands that the advertising be intensive and spread over a sufficiently broad range of hours. In our case, this condition was met only marginally for TV advertising.

There are various possibilities for further research. For example, researchers may examine the stability and sensitivity of advertising effectiveness under time aggregation. Additionally, the dynamic effects of different advertising themes in a campaign and the related wear-in/wear-out effects remain an issue to be analyzed. A third issue is whether long-term effects exist. Finally, possible threshold effects have potentially important implications. Increasing GRP intensity from an average of 300 for an active week to 500 or more may have a different impact than increasing GRP intensity from 200 to 300.

References


