NAVIGATING THE BRANDING LANDSCAPE:

THE RELEVANCE OF BRANDS AND BRAND MEASURES

FOR CONSUMERS AND FIRMS

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SYNOPSIS

1 Introduction

Brands are among a firm's most important marketing assets, and marketing managers name brand-building as one of their primary responsibilities (CMO Survey 2025). Not surprisingly, the total value of Interbrand's Top 100 brands has constantly risen since its first publication in 2000. Despite the economic turmoil of the past years, the cumulative brand value reached $3.4 trillion in 2024, compared to $988 billion in 2000 (Interbrand 2024a). However, this steady increase in the total brand value of the world's Top 100 brands over the past 25 years might mask ongoing challenges in marketing. As the two recent CMO Surveys reveal, marketing managers continue to struggle proving the financial performance impact of marketing actions and favor short-term gains over long-term brand building (CMO Survey 2024; CMO Survey 2025). This is because building and maintaining brand equity, defined as the value added of a branded product compared to a non-branded product (Farquhar 1989; Keller 1993), requires constant high investments, which, at the same time, are hard to quantify in terms of financial gains (Edeling and Fischer 2016; Mizik 2014). Challenges to evaluating the economic impact of brand equity arise from three main reasons. First, the value of brands as intangible assets is difficult to measure. Measurement methods range from non-monetary methods, such as consumer brand perceptions, to monetary methods, such as market share premium or Interbrand's brand value (Datta, Ailawadi, van Heerde 2017; Edeling and Fischer 2016; Mizik 2014). Second, the total financial performance impact of brand equity may only be realized in future periods (e.g., Mizik 2014; Nguyen and Feng 2021). Hence, a short-term perspective can overlook the long-term financial benefits that brands offer to firms. Finally, the economic impact of brand equity is heterogeneous across firms and industries (e.g., Fischer and Wies 2024; Mizik 2014), which further complicates the evaluation of its overall effect.

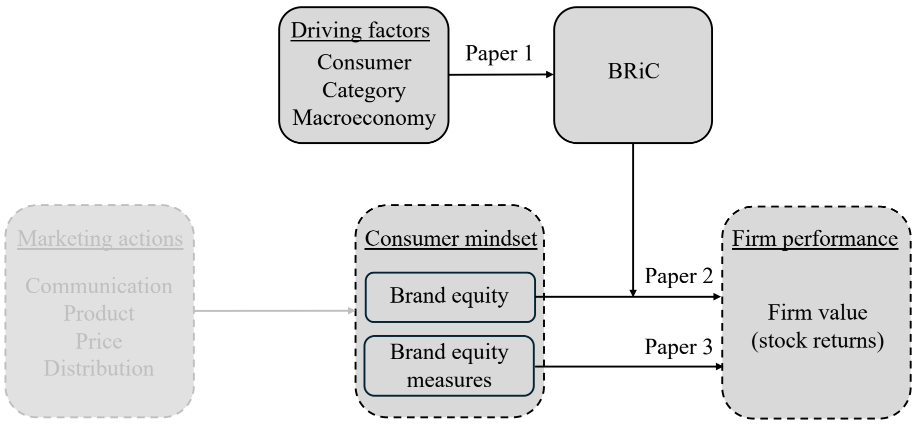
To underscore the financial accountability of brand equity, existing marketing literature has investigated its impact on firm value as a key future-oriented performance metric (e.g., Mizik 2014; Edeling and Fischer 2016; Rappaport 1998). Although findings demonstrate an overall positive effect of brand equity on firm value with an average elasticity of 0.33 (e.g., Edeling and Fischer 2016; Mizik 2014), results differ across types of brand measures (Johansson, Dimofte, and Mazvancheryl 2012), industries (Mizik 2014; Vomberg, Homburg, and Bornemann 2015), or firms (Fischer and Wies 2024). Anecdotal evidence supports this notion. Although, according to Interbrand, the brand value of McDonald's and BMW are close (McDonald's: $53 billion; BMW: $52 billion; Interbrand 2024b), the brand constitutes approximately 25% of McDonald's market capitalization, compared to approximately 92% for BMW (as of July 2025; Yahoo Finance 2025). Consequently, further investigation on the heterogeneous effects of brand equity and brand measures on firm value is warranted.

Simultaneously, marketing research and practice are beginning to suggest that "the era of brand is over" (WARC 2023), highlighting the increasing prevalence of product-focused advertising and the superior impact on firm value of customer-related assets (Binder and Hanssens 2015; Edeling and Fischer 2016; WARC 2023). However, no research has yet investigated how the relevance of brands for consumers has changed over time.

This cumulative dissertation investigates the antecedents and consequences of brand relevance and brand measures for consumers and firms. Fischer, Völckner, and Sattler (2010) define brand relevance in category (BRiC) as the extent to which the brand influences consumer decision-making across categories. They demonstrate that the relevance of the brand for consumers is driven by two main brand functions: the ability of brands to reduce consumers' perceived purchasing risk (risk reduction function) and the extent to which consumers can use brands to signal a self-concept or image (social demonstrance function). Previous marketing literature has highlighted the role of BRiC as a contingency factor along the brand value chain from marketing actions to consumer mindset and brand performance in terms of product-market outcomes (Johnen and Schnittka 2020; Keller and Lehmann 2003; Nguyen and Feng 2021; Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020). Despite this critical role, three important questions regarding BRiC remain unanswered. First, is BRiC a stable or dynamic construct changing over time? Second, if BRiC changes over time, what are the drivers of this change? Third, what is the role of BRiC in explaining financial market outcomes such as firm value? This dissertation addresses these questions in Papers 1 and 2. Given that the type of brand measure can also impact the brand equity-firm value link (Johansson, Dimofte, and Mazvancheryl 2012), Paper 3 compares traditional survey-based brand measures with newer social media-based real-time brand measures, addressing recent marketing research priorities (Marketing Science Institute 2022).

Figure 1 positions each dissertation project along the brand value chain (Edeling and Fischer 2016; Keller and Lehmann 2003).

Figure 1: Positioning of Dissertation Projects



Notes: Figure 1 positions the three dissertation projects along the brand value chain adopted from Edeling and Fischer (2016) and Keller and Lehmann (2003). Note that this dissertation does not address the first step in the brand value chain regarding the impact of marketing actions (grey shaded area).

Paper 1, titled "An Analysis of Brand Relevance Over Time" by Zeynep Karagür, analyzes whether brand relevance in different categories (BRiC) changes over time and what drives these changes in BRiC. The article builds on a unique dataset of large-scale consumer responses to BRiC and its brand functions (risk reduction and social demonstrance) over five waves in 2006, 2010, 2013, 2016, and 2019. The study combines various analytical methods from model-free descriptive analyses to simple t-tests and complex Bayesian hierarchical linear models. Findings show a positive trend in BRiC overall, with severe differences across categories. Wave-to-wave changes in BRiC across categories range from approximately -20% to +40%. These changes are primarily driven by the average brand strength (i.e., brand equity), the number of brands, the negative publicity in the category, and the business cycle.

Paper 2, titled "When Do Brands Matter More? The Moderating Effect of Brand Relevance on Firm Value" by Zeynep Karagür, investigates the effect of brand relevance as a moderating factor on the brand equity-firm value link. Having established that BRiC can significantly change over time in Paper 1, this research uses data on BRiC from several years, extending previous practice in marketing literature that considers BRiC as a time-invariant construct and measures it only once in longitudinal analyses (Nguyen and Feng 2021). Using a dataset of 1,537 firm-month observations for 49 unique firms and a stock market response model, the findings reveal a positive moderating effect of BRiC on the relationship between brand equity and firm value when utilizing several years of BRiC data. This finding adds to the moderating role of BRiC along the brand value chain and provides an underlying reason for the heterogeneous effects in the brand equity-firm value link.

Finally, in Paper 3, "Stronger Together – The Complementary Effect of Real-Time and Survey-Based Brand Measures on Firm Value" by Zeynep Karagür, I compare a social media-based real-time brand measure to a traditional survey-based brand measure in terms of their explanatory power on firm value. The brand measures are compared in three steps. First, both brand measures are contrasted conceptually. Second, model-free analyses, including correlational and graphical analyses, are applied. Finally, using vector autoregressive (VAR) models and their generalized forecast error variance decomposition (GFEVD), both brand measures are compared in terms of their ability to explain the variation in firm value across brands and industries. Therefore, I estimate three models for each brand: 1) a dual-brand metric model containing both brand measures, 2) a real-time brand metric model including only the real-time brand measure, and 3) a survey-based brand metric model with the survey-based brand measure only. Results demonstrate that combining real-time and survey-based brand measures in one model significantly increases the model's explanatory power, suggesting a complementary effect of both brand measures. This finding addresses recent calls for research comparing real-time brand measures to survey-based brand measures and linking the former to business outcomes (Marketing Science Institute 2022)

Table 1 gives an overview of the three dissertation projects.

Table 1: Overview of Dissertation Projects

Paper	Title	Author	Key objective
1	An Analysis of Brand Relevance Over Time	Zeynep Karagür	Analyzing the changes in BRiC and its drivers
2	When Do Brands Matter More? The Moderating Effect of Brand Relevance on Firm Value	Zeynep Karagür	Investigating the moderating effect of BRiC in the brand-equity-firm value link
3	Stronger Together – The Complementary Effect of Real-Time and Survey-Based Brand Measures on Firm Value	Zeynep Karagür	Comparison of real-time and survey-based brand measures and their relevance for explaining firm value

The following sections outline each dissertation project's motivation, objectives, methodology, main findings, and implications in more detail.

2 Summary of the Dissertation Projects

2.1 Paper 1: An Analysis of Brand Relevance Over Time

Despite the economic turmoil of the past years, the cumulative value of Interbrand's Top 100 most valuable brands has consistently grown, reaching $3.4 trillion in 2024 (Interbrand 2024a). However, not all categories are equally represented in the list of top brands. For example, among the top ten brands, five are technology brands and three are automotive brands, but there are no financial services or apparel brands (Interbrand 2024b). This suggests that brands may not be equally important across categories.

In marketing theory, this phenomenon is reflected in what Fischer, Völckner, and Sattler (2010) call brand relevance in category (BRiC), which describes the importance consumers place on the brand in their decision-making across different categories. The authors demonstrate that brand relevance differs across consumers, categories, and countries. Two brand functions mainly drive these differences: 1) risk reduction, i.e., the extent to which consumers use the brand to reduce their perceived purchasing risk, and 2) social demonstrance, i.e., the extent to which consumers use brands in a category to showcase a self-concept or image. Further consumer-specific factors (e.g., age and gender) and category-specific factors (e.g., the number of brands in a category) influence BRiC (Fischer, Völckner, and Sattler 2010). For example, when purchasing a car, consumers often refer to strong brands to reduce their perceived risk of making a wrong choice or to signal an image or status to others. In contrast, when consumers purchase everyday items like paper tissues, risk and status signaling tend to be low, so brands do not play a high role in these categories (Fischer, Völckner, and Sattler 2010).

Previous research shows that marketing activities such as advertising or product proliferation translate into higher brand-related marketing assets (e.g., consumers' trust in brands [CTB] or customer-based brand equity [CBBE]) in high-BRiC categories compared to low-BRiC categories (e.g., Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020). Similarly, brand love has a greater impact on firm profitability in high-BRiC categories than low-BRiC categories (Nguyen and Feng 2021). Consequently, marketing managers are well-advised to allocate their brand investments accordingly (Fischer, Völckner, and Sattler 2010).

So far, BRiC is considered a stable construct that remains unchanged over time (Fischer, Völckner, and Sattler 2010; Nguyen and Feng 2021). However, previous research has noted significant changes in BRiC in certain categories. For example, Fischer, Völckner, and Sattler (2010) conducted a replication study two and a half years after their initial study in 2006 and noted that BRiC significantly increased for bank accounts following the financial crisis in 2008. Similarly, changes in category dynamics, such as the introduction of new brands in the market, may influence BRiC over time. Given that BRiC impacts the effectiveness of marketing activities and brand-related assets (e.g., Nguyen and Feng 2021; Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020), an empirical investigation of whether, how, and why BRiC changes over time is warranted.

This study addresses this research gap by analyzing large-scale survey data on BRiC and the two brand functions from 5,053 respondents across 30 categories, spanning five waves from 2006 to 2019 (13,991 observations in total). This data is combined with brand data on 393 unique brands, macroeconomic data, and expert survey data. The analyses comprise two steps. First, using the data on BRiC and its brand functions, graphical analyses and simple t-tests reveal significant wave-to-wave changes for some categories. For example, following the Volkswagen emission scandal in 2015 (BBC 2015), BRiC in the medium-sized cars category significantly increased by 22%. Another notable change in BRiC occurred in the category of express delivery services, which grew by over 60% from 2006 to 2019. This increase in the relevance of brands for express delivery services may be attributed to the growth in e-commerce over the past years (Geuens 2025). However, only 16 (13.33%) out of 120 possible wave-to-wave category-level changes are significant.

Across categories, a positive trend in BRiC can be observed, which is supported by model-based analyses using Bayesian hierarchical linear models with respondent- and category-specific random intercepts and slopes. Additionally, the model-based analyses reveal that dynamic category- and macro-level variables moderate the relationship between the brand functions and BRiC, influencing BRiC overall. The average brand strength in the category, the number of brands, and negative publicity strengthen the relevance of the risk reduction function for BRiC. In contrast, social demonstrance becomes more important in times of economic upturns.

These findings bear several managerial implications. First, marketing managers are well-advised to track BRiC periodically for all categories in which they operate. Especially, after a category faces severe negative publicity, BRiC can significantly increase. This change might require allocating higher investments to the brand. Second, marketing managers can adapt their branding communications according to category- and macroeconomic factors. For example, following economic upswings, consumers value the symbolic function of brands more. Marketers can use this insight to focus on status signaling in their brand communications.

2.2 Paper 2: When Do Brands Matter More? The Moderating Effect of Brand Relevance on Firm Value

The cumulative value of the Top 100 brands by Interbrand reached an all-time high of $3.4 trillion in 2024, compared to $988 billion in 2000. Simultaneously, an estimated cumulative brand value potential loss of $3.5 trillion over the past 25 years can be attributed to firms' short-term focus (Interbrand 2024a). This short-term perspective is well-known in the marketing-finance literature, stemming from the challenges of quantifying the total financial impact of marketing actions and assets (Edeling and Fischer 2016; Edeling, Srinivasan, and Hanssens 2021; Mizik 2014). Marketing activities that aim to build marketing assets, such as the brand, require high initial and ongoing investments, which can negatively influence firms' financials (Edeling and Fischer 2016). At the same time, the long-term benefits of brand building are not directly noticeable and difficult to quantify, leading firms to prefer marketing initiatives with short-term gains (Mizik 2014).

To overcome this problem and underline the long-term benefits of brands, extant marketing literature has investigated the brand equity-firm value link. Although most results in previous research support a positive association between brand equity and firm value (e.g., Bharadwaj, Tuli, and Bonfrer 2011; Mizik and Jacobson 2008), contradicting findings in the form of null effects can also be observed (Luo, Raithel, and Wiles 2013). In a meta-analysis, Edeling and Fischer (2016) emphasize a high heterogeneity in the brand equity-firm value link, with elasticities ranging from -0.43 to 4.72. Accordingly, previous research demonstrates differences across firms (Fischer and Wies 2024) and industries (Ha, Song, and Erickson 2021; Mizik 2014; Vomberg, Homburg, and Bornemann 2015). For example, a stronger impact of brand equity on firm value can be observed in the service industry, where brands can serve as a means to mitigate purchasing risk (Vomberg, Homburg, and Bornemann 2015). This finding points to brand relevance in category (BRiC) as an underlying reason for the differences in the brand equity-firm value chain.

Defined as the importance of brands for consumer decision-making in different categories, BRiC acts as an important moderator along the brand value chain from marketing activities to customer mindset and brand performance (Datta, Ailawadi, and van Heerde 2017; Johnen and Schnittka 2020; Keller and Lehmann 2003; Nguyen and Feng 2021; Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020). In high-BRiC categories, consumers pay more attention to marketing activities of brands, resulting in higher brand-related assets (Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020). Similarly, brand-related assets translate into stronger brand performance (Nguyen and Feng 2021). Investors may anticipate this effect and thus be more attentive to changes in brand equity in high-BRiC categories, leading to differences in brand equity's impact on firm value.

Based on 1,537 firm-month observations by 49 unique firms, the findings of a stock return response model using a Gaussian copula correction for the potential endogeneity of brand equity support the hypothesis that BRiC positively moderates the brand equity-firm value link. Changes in brand equity are more relevant to investor decisions in high-BRiC categories.

Interestingly, the moderating effect of BRiC becomes insignificant if BRiC is considered a time-invariant construct and only BRiC values from the final year are applied in the analyses.

Additionally, the results of this research indicate a negative but insignificant main effect of brand equity, which contradicts most findings in previous literature. Conditional effect analysis using a Johnson-Neyman plot (Johnson and Neyman 1936) reveals that the negative effect of brand equity is only significant for low levels of BRiC. In contrast, for high levels of BRiC, the slope of brand equity becomes less negative but insignificant. This finding suggests that the heterogeneous effects observed in previous studies could be attributed to BRiC, implying that the main effect of brand equity on firm value may vary depending on the sample of firms.

The implications of this research for theory and practice are threefold. First, from a theoretical perspective, the current research findings extend the previous literature on the moderating role of BRiC along the brand value chain to firm value. Second, this research cautions marketing researchers against considering BRiC as a static construct in longitudinal analyses, as this approach might mask the true effect of BRiC. Finally, the results alleviate concerns of marketing managers in firms of high-BRiC categories by highlighting that in these categories, brand investments do not elicit adverse investor reactions even in the short run.

2.3 Paper 3: Stronger Together – The Complementary Effect of Real-Time and Survey-Based Brand Measures on Firm Value

Measuring consumer perception about brands (i.e., customer-based brand equity [CBBE]) is crucial in marketing theory and practice. Over the years, many commercial providers have emerged that measure consumer brand perceptions using large-scale surveys. Young & Rubicam's Brand Asset Valuator (BAV), Harris Interactive's EquiTrend, and YouGov's BrandIndex are the most prominent providers. However, survey-based methods have the disadvantage that they are costly to collect and thus mostly only available at a non-granular level (e.g., quarterly or annually). Hence, they are unlikely to capture the short-term effects of marketing actions on consumer brand perceptions. Consequently, recent research priorities call for more studies on real-time and dynamic brand measures (Marketing Science Institute 2022). Such real-time brand measures can be built on social media data, which is increasingly gaining importance as a platform that enables consumers to express their opinions about brands (Fossen and Schweidel 2019; Hewett et al. 2016). A prominent recent example is the GameStop short squeeze on January 28, 2021, where Reddit users initiated a coordinated buying of the company's stocks, increasing the stock price by over 1800% (Davies 2021). Not surprisingly, firms are moving towards social media analytics with an estimated market size of $61.95 billion by 2032 (Fortune Business Insights 2025). But how are real-time and survey-based brand measures related? And how do both brand measures perform in explaining firm value?

This research compares the newly developed social media-based brand reputation tracker by Rust et al. (2021) to the survey-based brand measure, BrandIndex, by YouGov. Overall, the findings suggest a complementary effect of combining both brand measures. First, a low and negative correlation between the two brand measures is observed. Second, building on 4,290 brand-week observations, the results of vector autoregressive (VAR) models and their generalized forecast error variance decomposition (GFEVD) demonstrate that combining real-time and survey-based brand measures significantly improves the model's explanatory power by 38% compared to the single-brand metric models. Within the dual-brand metric model that includes both brand measures, the survey-based brand measure accounts for a slightly higher portion of the variance in firm value. Survey-based brand measures are even more relevant for service brands. On the contrary, the explanatory power of real-time brand measures exceeds that of survey-based brand measures for manufacturing brands. Considering the current trend towards social media analytics, this research cautions against neglecting surveys as they still bear relevance in explaining firm value, especially for service brands.

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PAPER 1: AN ANALYSIS OF BRAND RELEVANCE OVER TIME

Author: Zeynep Karagür

ABSTRACT

Research shows that the effectiveness of marketing activities differs across categories contingent on the importance of the brand in the consumer purchase decision process within the category, i.e., the brand relevance in the category (BRiC). This research is the first to investigate BRiC over time. Results indicate that brands, on average, become more relevant over time, though with heterogeneity across categories. Using a Bayesian hierarchical model based on a multi-source dataset that combines consumer survey data from 3,785 respondents (8,977 observations) in 28 categories with data on 393 unique brands, the author finds that consumer-level factors, dynamic category-level factors, and macro-level factors affect BRiC. Confirming previous findings, the two functions of the brand (1) risk reduction and (2) signaling a self-concept are the main drivers of BRiC. Consumers' age, the average category brand strength, the number of brands in the category, negative publicity in the category, and the business cycle either strengthen or weaken the relationship between the two brand functions and BRiC. These findings bear important implications for managers when making brand investment and communication decisions.

Keywords: Brand relevance in category, business cycle, category characteristics, hierarchical modeling

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1 Introduction

Brands belong to a firm's most valuable assets, contributing positively to its financial performance and valuation (Edeling and Fischer 2016). Thus, it is not surprising that firms invest significantly in brand-building activities. Despite the global economic turmoil in recent years, Interbrand's Best Global Brands report in 2023 highlights an increase of 16% in the total value of the Top 100 Global Brands, the largest yearly increase so far (Interbrand 2023). At the same time, though, marketing experts articulate a decline in the importance of brands for companies compared to other assets such as customer equity (Binder and Hanssens 2015; WARC 2023). One possible explanation for these contradicting views might lie in the varying relevance of brands for consumers in different categories (Fischer, Völckner, and Sattler 2010).

Fischer, Völckner, and Sattler (2010) introduced the concept of brand relevance in category (BRiC), which describes the extent to which the brand, compared to other decision criteria like the price, influences consumer decision-making. They emphasize that BRiC is primarily driven by two brand functions: the relevance of the brand for reducing consumer purchasing risk (i.e., the risk reduction function) and its relevance for signaling a consumer's self-concept or image (i.e., the social demonstrance function). Brand relevance differs across categories, but not across different brands within a category. For instance, when purchasing a car, consumers often focus on the brand name because it reduces their risk of making a poor choice and can serve as a status symbol in social settings. However, when buying everyday items like paper tissues, the perceived purchasing risk and the potential of status signaling are low, so other criteria, such as price or availability, tend to be more important than the brand. Given the higher relevance of the brand for consumers in categories like cars, marketing managers might be required to allocate brand-building efforts accordingly (Fischer, Völckner, and Sattler 2010).

In line with this reasoning, research in recent years highlights the moderating role of BRiC in the brand value chain from marketing activities to customer brand perceptions and brand performance (Johnen and Schnittka 2020; Keller and Lehmann 2003; Nguyen and Feng 2021; Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020). For example, marketing activities such as advertising, price, distribution, new product introductions, and product proliferation translate into higher consumers' trust in brands (CTB) and customer-based brand equity (CBBE) in high-BRiC categories than in low-BRiC categories (Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020). Similarly, the effect of brand love on firm profitability is stronger for high-BRiC categories (Nguyen and Feng 2021).

While most studies investigate the moderating effect of BRiC in a cross-sectional setting, Nguyen and Feng (2021) analyze longitudinal data but measure BRiC only once. Their underlying assumption is that BRiC should be stable over time. However, to the best of my knowledge, no research so far has extensively investigated whether BRiC is stable or changes over time. This research aims to fill this gap. There is one exception that examined BRiC over two time periods. Specifically, Fischer, Völckner, and Sattler (2010) report the findings of a replication study two and a half years after their first study in 2006. They indicate a high correlation (0.938, $p < 0.05$) between the two points in time, but at the same time, they find significant differences for certain categories. For example, the authors note a significant increase in BRiC for bank accounts in the UK, a change that can be attributed to the financial crisis in 2008. This may have increased consumer uncertainty and perceived risk associated with bank accounts, leading to higher brand relevance over time (Fischer, Völckner, and Sattler 2010). In addition, Nguyen and Feng (2021) report a lower correlation between their BRiC values and the initial values of Fischer, Völckner, and Sattler (2010) from 2006 (0.780; $p < 0.001$). While, on average, BRiC has increased by 13% since 2006, changes in BRiC over time across categories range from -6% to +30% (Nguyen and Feng 2021). These initial findings suggest three important characteristics regarding the behavior of BRiC over time. First, while BRiC might be a relatively stable construct in the short term (Fischer, Völckner, and Sattler

2010), significant changes in the long term may be notable (Nguyen and Feng 2021). Second, changes in BRiC over time can differ across categories (Fischer, Völckner, and Sattler 2010; Nguyen and Feng 2021). Lastly, changes in BRiC seem to be driven by category-specific and overall macroeconomic factors (Fischer, Völckner, and Sattler 2010). This research adds to these initial findings on the behavior of BRiC over time by (1) extending the time period to five waves of data collection and (2) investigating the underlying reasons for the changes in BRiC over time. Specifically, this research aims to answer the following research questions:

(1) How is BRiC changing over time, both in general and in different categories?

(2) What variables are associated with the changes in BRiC, and how?

To address these research questions, I combine survey data on BRiC and the brand functions from 5,053 respondents on 30 categories over five waves spanning from 2006 to 2019 (13,991 observations in total) with brand data on 393 unique brands, macroeconomic data, and expert survey data. The final dataset builds on 8,977 observations from 3,785 respondents in 28 categories. So far, only two studies have cross-sectionally analyzed the drivers of BRiC in the business-to-consumer (Fischer, Völckner, and Sattler 2010) and business-to-business contexts (Backhaus, Steiner, and Lügger 2011). In the business-to-consumer context, which is the focus of the current research, category-level factors such as the number of brands or the functional homogeneity of different brands within the category are related to BRiC (Fischer, Völckner, and Sattler 2010). However, these factors may change over time depending on developments in the category, such as the entry of new brands into the market. Thus, this research differs from previous literature in that it considers BRiC as a dynamic construct that can change over time and investigates the impact of *dynamic* (i.e., time-varying) factors on BRiC.

The contribution of this research to theory and practice is twofold. First, this research extends previous literature on BRiC by investigating how BRiC develops over time. While

BRiC remains relatively stable for most categories, notable short-term or long-term changes can be observed in specific categories. These findings caution that measuring BRiC at one point in time for longitudinal analyses (Nguyen and Feng 2021) may lead to misleading conclusions for theory and practice. Attention should be especially given in situations where categories face high negative publicity, which strengthens the importance of the risk reduction function of the brand for consumers and increases BRiC. For example, following the Volkswagen emission scandal, which negatively impacted the entire category (Bachmann et al. 2023), BRiC in the cars category increased by 22% (by 0.84 points on a 7-point scale) from 2013 to 2016. This, in turn, may affect how firms benefit financially from brand-related investments (e.g., Nguyen and Feng 2021). On the contrary, demonstrating a self-concept or image (e.g., status) gains relevance for consumers during economic upturns, supporting earlier research findings on the impact of the business cycle on consumer preferences for branded products (e.g., Scholdra et al. 2022). Hence, the second contribution of this research lies in highlighting the impact of dynamic category-specific and macroeconomic factors on BRiC. Managers can use these insights to design their brand-building activities by adjusting brand-related expenditures over time. In addition, the insights provide guidance on when to emphasize either the risk reduction or social demonstrance functions of the brand in brand communications, depending on the macroeconomic climate, for instance.

2 Theoretical Background

2.1 BRiC and the Brand Functions

The concept of BRiC was introduced and tested across various countries by Fischer, Völckner, and Sattler (2010) to account for the differing importance of the brand in consumers' decision-making across categories. In a cross-sectional study with data from 2006, they found that BRiC is the highest in the U.S. compared to France, Spain, the U.K., and Japan, and for durables compared to services and FMCG. Although the authors acknowledge BRiC's similarity to other brand-related constructs, such as brand equity, the key distinction is that BRiC remains constant across brands in the same category and differs only across categories (Fischer, Völckner, and Sattler 2010; Keller 1993). Still, the concept of BRiC builds on the idea that brands provide benefits to consumers. Fischer, Völckner, and Sattler (2010) state two main brand functions that positively contribute to BRiC: risk reduction and social demonstrance, whereby risk reduction has a larger effect on BRiC than social demonstrance.

Risk reduction. From an information economics perspective, firms possess an information advantage over consumers regarding the performance of their products. This information asymmetry necessitates that consumers rely on signals provided by firms when making purchasing decisions (Erdem and Swait 1998; Kirmani and Rao 2000). Previous research indicates that a wide range of marketing mix elements, including brands (e.g., Erdem and Swait 1998), can serve as signals for product performance (see Kirmani and Rao 2000 for an overview). Brands identify the product manufacturer and help consumers build product knowledge and experience. Consumers can then utilize their accumulated knowledge about a brand to infer product performance, thereby simplifying their decision-making process and reducing their purchasing risk (Erdem and Swait 1998; Keller and Swaminathan 2019). Products are typically classified into search, experience, and credence goods. While consumers can evaluate search goods based on product attributes like design and ingredients, experience and credence goods cannot be easily assessed before purchase and use (Fischer, Völckner, and Sattler 2010; Keller and Swaminathan 2019; Nelson 1970). Consequently, in these categories, consumers may perceive a higher purchasing risk due to greater uncertainty regarding product performance (Fischer, Völckner, and Sattler 2010). In addition, the perceived risk within specific categories may be greater either because consumers view the consequence of a purchase mistake as more significant or due to larger quality differences among alternatives in a category (Datta, Ailawadi, and van Heerde 2017). Thus, in categories with higher perceived purchasing risk, such as costly categories like cars, consumers place higher relevance to the brand as a quality signal to mitigate their risk (Fischer, Völckner, and Sattler 2010).

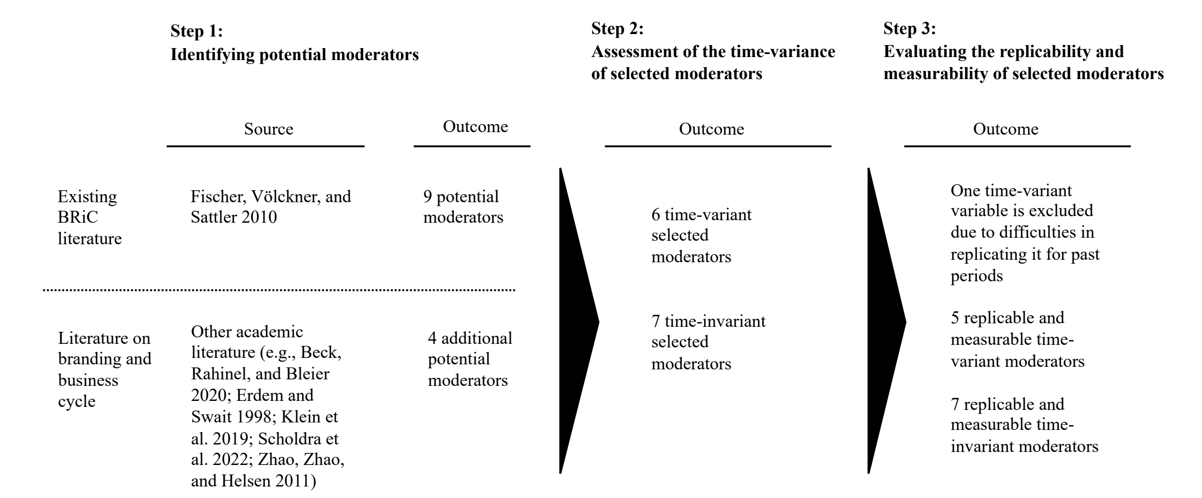
Social demonstrance. Brands can serve as a symbolic device to communicate a particular self-concept, an image, or status (Belk 1988; Levy 1959; Veblen 1899). Different brands occupy various associations in the consumers' minds based on product or service attributes, benefits, and attitudes (Keller 1993). Benefits denote the advantages that consumers derive from a product or service, including the symbolic advantage consumers can gain by using a particular brand to communicate or enhance their self-concept (Fischer, Völckner, and Sattler 2010; Escalas and Bettmann 2005; Grubb and Grathwohl 1967; Keller 1993). Consumers choose specific brands for self-expression (Escalas and Bettmann 2005; Grubb and Grathwohl 1967) and to signal a group membership (Bearden and Etzel 1982), or they may avoid certain brands to distance themselves from undesirable groups (Berger and Heath 2007). This symbolic function of the brand should especially be relevant for products that offer a certain level of differentiation and are highly visible to other consumers (e.g., cars), leading to differences across categories (Fischer, Völckner, and Sattler 2010; Keller 1993).

In general, risk reduction and social demonstrance positively relate to BRiC, meaning that the more consumers use brands in a category to reduce their risk or demonstrate a self-concept, the higher the relevance of the brand in that category (Fischer, Völckner, and Sattler 2010). Fischer, Völckner, and Sattler (2010) also demonstrate that consumer-level (e.g., age) and category-level (e.g., frequency of new product introductions) factors moderate the relationship between the two brand functions and BRiC or directly impact BRiC[1]. In the following, I will use this as a starting point to identify and select further moderating factors to investigate the changes in BRiC over time.

2.2 Selection of Moderating Factors

Figure 1 presents the three steps involved in identifying and selecting potential moderating factors of the relationship between the brand functions and BRiC over time.

Figure 1: Steps of Selecting Potential Moderating Factors



In the first step, I scanned existing marketing literature to generate a list of potential moderators. I started with the foundational work of Fischer, Völckner, and Sattler (2010), who identified nine driving variables of BRiC. Additionally, other literature related to branding (e.g., Beck, Rahinel, and Bleier 2020; Erdem and Swait 1998; Zhao, Zhao, and Helsen 2011) and the business cycle (e.g., Scholdra et al. 2022) provided guidance on further potential moderators. In total, 13 potential moderators were identified based on previous literature. In the next step, I

[1] Although Fischer, Völckner, and Sattler (2010) do not directly model category-level factors as moderators on the relationship between the brand functions and BRiC, their line of theoretical argumentation also suggests a moderating effect. For example, the authors identify new product introductions as one category-level driver of BRiC and argue that "The brand name may provide the means to reduce the risk associated with the evaluation of a newly introduced product." (Fischer, Völckner, and Sattler 2010, p. 827). This implies that the category-level factor frequency of new product introductions might strengthen the relationship between risk reduction and BRiC and thereby impact BRiC. Thus, I rather consider category-level factors as moderators of the relationship between the two brand functions and BRiC.

assessed the variability of the selected moderators over time. As data on BRiC and the brand functions are available for five waves between 2006 and 2019, assessing the variability of each variable over time is necessary to allocate the moderators to the respective data collection waves correctly. Finally, for moderators that might change over time, I evaluated the replicability and measurability of the moderator for previous periods. Replicability and measurability assess whether past values for the moderator can be reconstructed or not. Only moderators that do not change over time or can be reconstructed for past periods are considered. This procedure resulted in the selection of twelve moderators that can be categorized into three levels: consumer-level, category-level, and macro-level (see Appendix A for details).

2.2.1 Consumer-level factors

Fischer, Völckner, and Sattler (2010) find that consumer heterogeneity influences the relationship between the brand functions and BRiC. The brand's risk reduction function gains importance for older and female consumers, as both consumer groups are more risk-averse. In contrast, the role of social demonstrance for BRiC is greater for younger consumers who are in the process of advancing personally and professionally and for whom projecting a particular image is especially important (Fischer, Völckner, and Sattler 2010). Past research also shows that education negatively affects the usage of brand-related information (Klein et al. 2019), leading to differences across consumers. Hence, I select *age, gender, and education* as consumer-level moderating factors[2].

2.2.2 Category-level factors

Additionally, Fischer, Völckner, and Sattler (2010) identify the following category-level factors influencing BRiC: the degree of homogeneity in functional benefits, the number of available brands, the frequency of new product introductions, the visibility of consumption, the

[2] In this research, consumer-level factors (i.e., age, gender, and education) are considered time-invariant because respondents differ across waves of data collection, leading to a repeated cross-sectional design.

ability to judge quality ex-ante, decision involvement, and group decision-making. For example, the presence of more brands in the category and frequent new product introductions increases consumers' uncertainty and risk of making a wrong purchase. In such circumstances, brands can mitigate consumers' perceived risk by providing a quality signal and reducing the effort required to evaluate alternatives (Erdem and Swait 1998; Fischer, Völckner, and Sattler 2010). Similarly, the visibility of consumption to others positively influences BRiC as consumers can leverage brands more effectively to showcase their self-concept in highly visible categories (Bearden and Etzel 1982; Fischer, Völckner, and Sattler 2010).

The category-level factors proposed by Fischer, Völckner, and Sattler (2010) can be categorized into two types depending on their temporal variability: *static* and *dynamic* category-level factors. *Static* category-level factors include the *visibility of consumption, the ability to judge quality ex-ante, decision involvement, and group decision-making*. These factors represent core characteristics of the category that remain stable over time. For instance, products in a category may be categorized as either visible or not, and the quality of the product can be evaluated before consumption or not. In contrast, *dynamic* category-level factors, which include the homogeneity of functional benefits, the number of available brands, and the frequency of new product introductions, are subject to changes over time, e.g., when new brands enter the market. This research adds to previous work that considers both types of category-level factors as stable in a cross-sectional setting (Fischer, Völckner, and Sattler 2010) by accounting for changes in dynamic category-level factors over time. Thus, dynamic category-level factors must be replicable and measurable for all data collection waves, constraining variable selection and operationalization. For instance, capturing the homogeneity of functional benefits for past periods is challenging. Therefore, I extend the concept of homogeneity of functional benefits proposed by Fischer, Völckner, and Sattler (2010) to capture how consumers perceive different brands in a category overall by introducing the variable *variation in brand* *strength*. Brand strength reflects different dimensions by which consumers perceive the brand's image and performance (Backhaus and Fischer 2016; Keller 1993). Hence, brand strength variation measures consumers' perceived homogeneity (or heterogeneity) of different brands in a category. *Number of available brands* can be reconstructed for past periods using proxies (see data section). In contrast, measuring the frequency of new product introductions for past periods is problematic for the entire range of categories included in this study and, therefore, excluded.

In addition, previous research highlights the importance of brand equity and brand leaders in reducing consumer uncertainty and enhancing feelings of self-control (Beck, Rahinel, and Bleier 2020; Erdem and Swait 1998). These effects are captured by the category's *average brand strength* and *the power of the category leader*. Dynamics within a category (e.g., the introduction of new brands to the market) can change the overall perception of the category. For example, in the car industry, if new entrants with weak brand strength enter the industry, they may alter consumer perceptions of brands across the entire category. This underscores the importance of brand strength in the analysis. Similarly, negative publicity about brands, such as product-harm crises, influences consumer choice of brands (Zhao, Zhao, and Helsen 2011). Hence, I also consider the average *negative publicity* in the category as an additional dynamic category-level factor.

2.2.3 Macro-level factors

Although not directly linked to BRiC, existing literature highlights the impact of macroeconomic fluctuations (i.e., the business cycle) on consumer behavior (see Dekimpe and Deleersnyder 2018 for an overview). Depending on the macroeconomic situation, consumers adapt their budget allocations (Du and Kamakura 2008), category purchases (Kamakura and Du 2012), purchase volume, store preferences, and brand preferences (Scholdra et al. 2022). During economic downturns, consumers spend less on durables (Deleersnyder et al. 2004; Dutt and Padmanabhan 2011) and shift their purchases towards private labels (Lamey et al. 2007;

Scholdra et al. 2022), products on price promotion (Cha, Chintagunta, and Dhar 2016) and cheaper store formats (Cha, Chintagunta, and Dhar 2016; Lamey 2014). Conversely, in times of economic upswings, consumers spend more on branded products (Scholdra et al. 2022) and become less price-aware and price-sensitive (Estelami, Lehmann, and Holden 2001; van Heerde et al. 2013). At the brand level, Rajavi, Kushwaha, and Steenkamp (2023) identify strategic brand factors that explain differences in the success of brands during economic expansions and contractions. For example, the authors find that market leader brands outperform other brands during economic expansions. This research contributes to the existing business cycle literature by examining the impact of the *business cycle* on the relevance of brands for consumers across different product categories. If consumers are willing to spend more on branded products and are less price-sensitive during economic growth, the relevance of brands may also increase.

Table 1 summarizes the selected moderating factors and their sources.

Table 1: Overview of the Selected Moderator Variables

Moderating factor	Original variable	Source
Consumer-level factors		
Age	Age	Fischer, Völckner, and Sattler (2010)
Gender	Gender	Fischer, Völckner, and Sattler (2010)
Education	Education	Klein et al. (2019)
Static category-level factors		
Visibility of consumption	Visibility of consumption	Fischer, Völckner, and Sattler (2010)
Ability to judge quality ex-ante	Ability to judge quality ex-ante	Fischer, Völckner, and Sattler (2010)
Decision involvement	Decision involvement	Fischer, Völckner, and Sattler (2010)
Group decision-making	Group decision-making	Fischer, Völckner, and Sattler (2010)
Dynamic category-level factors		
Brand strength average	Brand equity	Erdem and Swait (1998)
Variation in brand strength	Homogeneity of functional benefits	Fischer, Völckner, and Sattler (2010)
Power of category leader	Brand leader, market leader brands	Beck, Rahinel, and Bleier (2020); Rajavi, Kushwaha, and Steenkamp (2023)
Number of brands	Number of brands	Fischer, Völckner, and Sattler (2010)
Negative publicity	Product-harm crisis	Zhao, Zhao, and Helsen (2011)
Macro-level factors		
Business cycle	Business cycle	e.g., Scholdra et al. (2022)

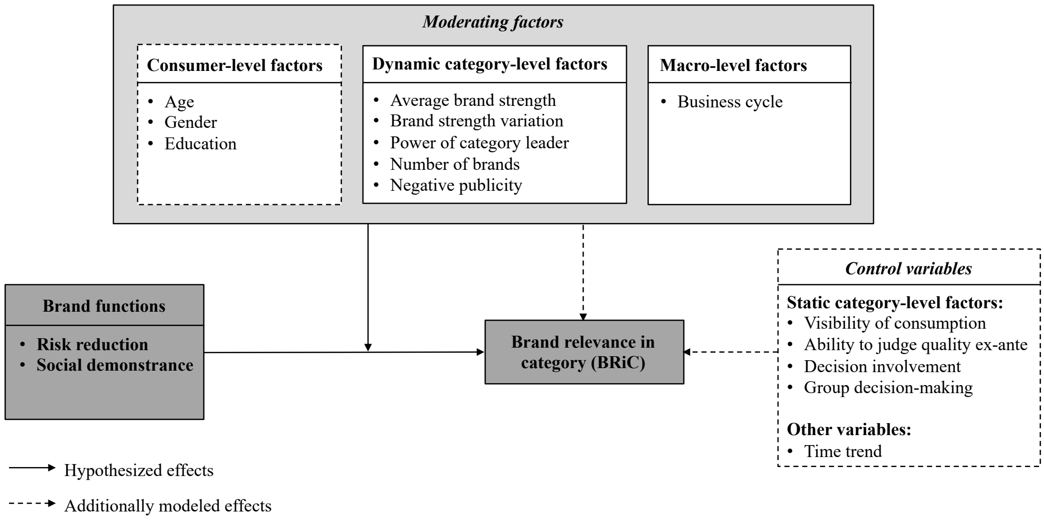
3 Conceptual Framework

3.1 Accessibility-Diagnosticity Framework

BRiC is defined as the extent to which the brand influences consumer decision-making across different categories (Fischer, Völckner, and Sattler 2010). In other words, BRiC describes the likelihood that consumers will consider the brand as an input in their decision-making process. This notion aligns with the Accessibility-Diagnosticity framework by Feldman and Lynch (1988), which posits that an input will be utilized for judgment and decision-making when (1) it is readily accessible in memory and retrievable and (2) the input is perceived as diagnostic for the specific decision. Diagnosticity refers to the ability of an input to distinguish between alternatives, such as low- and high-quality brands, and is overvalued when the input is highly accessible (Feldman and Lynch 1988; Herr, Kardes, and Kim 1991). Within the context of BRiC, the Accessibility-Diagnosticity framework suggests that the brand will have greater relevance as a decision criterion if brands are more salient to consumers and/or more indicative of distinguishing between alternatives (e.g., differentiating between low- and high-quality brands) in the category.

Figure 2 displays the conceptual framework. It includes three levels of factors as moderators on the association of risk reduction and social demonstrance and BRiC: consumer-level, category-level, and macro-level. As the changes in BRiC over time are the focus of the current research, hypotheses based on the Accessibility-Diagnosticity framework are derived only for the moderating effect of time-varying factors, i.e., the dynamic category-level and macro-level factors. Following past research (Fischer, Völckner, and Sattler 2010; Klein et al. 2019), consumer-level factors are also included as moderators. Finally, static category variables are only included as control variables to account for their direct effects on BRiC (Fischer, Völckner, and Sattler 2010).

Figure 2: Conceptual Framework



3.2 Hypotheses Development

3.2.1 Dynamic category-level factors

Average brand strength. Following past research (Backhaus and Fischer 2016; Stäbler and Fischer 2020), I define customer-based brand equity as brand strength in this study. Accordingly, brand strength encompasses different dimensions of how consumers perceive the brand's image and performance (Backhaus and Fischer 2016; Keller 1993). From a consumer psychology perspective, high brand strength is necessary for consumers to capitalize on the risk-reduction function of brands (Erdem and Swait 1998). Similarly, only brands evaluated as high-value and overall positive can provide consumers with a symbolic value to express their self-concept. A category with high average brand strength will contain stronger and more popular brands. Thus, brands will be more accessible and diagnostic to consumers. Previous studies show that when brand-related information is more accessible, it is more likely to be utilized (Menon and Raghubir 2003). Hence, a high average brand strength in the category will positively moderate the associations of risk reduction or social demonstrance and BRiC.

Brand strength variation. According to the Accessibility-Diagnosticity framework diagnosticity, i.e., the extent to which information can help to differentiate among alternatives, increases its utilization (Feldman and Lynch 1988; Herr, Kardes, and Kim 1991). A high variation in brand strength between brands in a category facilitates consumers to discriminate between low- and high-quality brands and consume or avoid specific brands to display their self-concept. For example, if there are significant differences in brand strength among car brands, it is easier for consumers to distinguish between them. In addition, a high variation between brands increases consumers' perceived purchasing risk of making a wrong choice, which enhances the relevance of brands in reducing this risk (Datta, Ailawadi, and van Heerde 2017; Fischer, Völckner, and Sattler 2010). On the other hand, if brands in a category are similar and interchangeable, purchasing risk is low, and consumers cannot use brands to differentiate themselves from others. Thus, I expect brand strength variation to strengthen the association of risk reduction or social demonstrance and BRiC.

Power of category leader. Following past research that defines brand leaders "as those that lead their category in market share" (Beck, Rahinel, and Bleier 2020, p. 873), category leaders in this research represent brands with the highest perceived brand strength compared to other brands in a category. Accordingly, the power of the category leader is defined as the distance in brand strength between the strongest and second-strongest brands in the category. A larger disparity between the category leader and other brands may heighten consumer uncertainty and perceived purchasing risks for non-leader brands (Datta, Ailawadi, and van Heerde 2017). Therefore, consumers may prefer to purchase the category leader, which is perceived as the best-performing brand in the category, to mitigate their risk. Similarly, category-leader brands can restore consumers' sense of control (Beck, Rahinel, and Bleier 2020), which may be beneficial in situations of heightened risk. Additionally, stronger brands have higher awareness and a more favorable image (Keller 1993), which consumers can use to express status and prestige more effectively. Overall, these mechanisms should drive the relevance of brands in the category as a decision criterion, as the diagnosticity and accessibility of the brand increase.

For example, even though newer brands in the car industry offer similar functionality to established brands, consumers still prefer established and strong brands. Hence, I hypothesize a positive moderating effect of the power of the category leader on the relationship between risk reduction or social demonstrance and BRiC.

Number of brands. Consumers possess only a limited capacity to evaluate alternatives (Bettman, Luce, and Payne 1998). As the number of brands increases, assessing all alternatives becomes more complex and challenging (Iyengar and Lepper 2000), resulting in greater uncertainty for consumers. In such situations, brands are particularly beneficial as they simplify decision-making by reducing the time and effort spent on evaluating alternatives (Erdem and Swait 1998; Fischer, Völckner, and Sattler 2010). This increases the diagnosticity of brands in reducing purchasing risk. Hence, I expect that the number of brands will strengthen the relationship between risk reduction and BRiC. Concerning the association of social demonstrance and BRiC, the moderating effect of the number of brands in a category is unclear. The role of brands as a symbolic device might be influenced more by the strength of the brands within the category than by the sheer number of brands. I, therefore, expect no effect of the number of brands on the relationship between social demonstrance and BRiC.

Negative publicity. Negative publicity generates attention to brands (Backhaus and Fischer 2016) and leads to increased media coverage (Stäbler and Fischer 2020). As a result, the accessibility of brands in the minds of consumers increases. At the same time, negative publicity about brands heightens consumers' risk aversion and uncertainty about product quality (Zhao, Zhao, and Helsen 2011), decreases the image of the affected brand (Backhaus and Fischer 2016), and may extend to other brands in the category, impacting the entire category (Bachmann et al. 2023; Roehm and Tybout 2006). Consequently, consumers may focus more on brands to reduce their risk and prefer brands that are not affected by negative publicity in the category (Zhao, Zhao, and Helsen 2011), which increases the brand's diagnosticity for risk reduction. In contrast, the negative spillover to other brands in the category may diminish the symbolic value of brands within the entire category (Roehm and Tybout 2006), thereby reducing the brand's diagnosticity for social demonstrance. Using the example of the Volkswagen emission scandal in 2015, Bachmann et al. (2023) demonstrate two opposing effects of the scandal on other German car brands. While there is a negative reputational spillover effect on other German car brands, there is also a positive sales effect due to substitution. Following this reasoning, I expect a two-sided impact of negative publicity. While negative publicity is expected to strengthen the relationship between risk reduction and BRiC, it might reduce the relevance of social demonstrance.

3.2.2 Macro-level factors

Previous research suggests that during economic upturns, consumers tend to buy more branded products, even if their budget remains constant (Scholdra et al. 2022). This may lead to a higher accessibility of brands in the consumers' minds. Research suggests that one potential explanation for the increased preference for branded products is that during economic upswings, which benefit the overall population, consumers may feel pressured to buy more branded products to uphold their social status (Kamakura and Du 2012; Scholdra et al. 2022). As a result, brands become more diagnostic in displaying status, which should strengthen the relationship between social demonstrance and BRiC. Conversely, the impact of the business cycle on the relationship between risk reduction and BRiC can be either positive or negative. On the one hand, consumers tend to buy more branded products during economic upturns (Scholdra et al. 2022). Branded products are generally more costly than non-branded products, which might increase consumers' perceived purchasing risk. Brands can help mitigate the risks associated with making these expensive purchases (Fischer, Völckner, and Sattler 2010), thereby increasing the diagnosticity of the brand for risk reduction. On the other hand, consumers have higher disposable incomes during economic upturns (Kamakura and Du 2012), which may lower their perceived purchasing risk and the role of brands in mitigating it. Consequently, the business cycle might either strengthen or weaken the relationship between risk reduction and BRiC.

Table 2 summarizes the expected effects.

Table 2: Summary of the Expected Effects

Variable	Effects on the association of risk reduction and BRiC	Effects on the association of social demonstrance and BRiC
Dynamic category-level factors		
Average brand strength	(+)	(+)
Brand strength variation	(+)	(+)
Power of category leader	(+)	(+)
Number of brands	(+)	(+/–)
Negative publicity	(+)	(–)
Macro-level factors		
Business cycle	(+/–)	(+)

Note: (+) indicates an expected positive moderating effect. (–) indicates an expected negative moderating effect.

4 Methodology

4.1 Data

This research utilizes survey data enriched with secondary data to identify how BRiC has changed over time. Table 3 shows the various data sources for the different variables. First, consumer-level survey data on BRiC, risk reduction, social demonstrance, and consumer demographics were collected in Germany across several categories by an external market research provider across five waves, namely in 2006, 2010, 2013, 2016, and 2019. This dataset constitutes the basis for identifying how BRiC has evolved and is matched with a wide range of secondary and expert survey data from Germany. Second, I obtained brand data from the market research company YouGov for the dynamic category-level variables. Third, the business cycle was constructed using macroeconomic data on GDP expressed in seasonally adjusted constant prices from the Federal Statistical Office in Germany. Brand and macroeconomic data lag the BRiC data by one year and come from 2009, 2012, 2015, and 2018. Lastly, a survey was conducted among marketing experts from academia to collect the static category-level variables.

Table 3: Summary of Data Sources and Measures

Data source	Data	Frequency of data collection	Time frame	Aggregation level	Number of categories
External market research provider	Data on BRiC, the brand functions, and consumer-level factors	Waves	2006, 2010, 2013, 2016, 2019	Individual	30
YouGov	Data on dynamic category variables	Daily	2009, 2012, 2015, 2018	Brand	28
German Federal Statistical Office	Data on business cycle	Yearly	2009, 2012, 2015, 2018	Year	–
Expert survey	Data on static category variables	–	–	Category	30

4.1.1 BRiC, risk reduction, social demonstrance, and consumer-level factors

An external market research provider collected consumer-level survey data on respondents' demographics (age, gender, and education), BRiC, and the two brand functions risk reduction and social demonstrance for several categories covering FMCG, services, durables, and retail in Germany over five waves in 2006, 2010, 2013, 2016, and 2019. Respondents differed in each wave, resulting in a repeated cross-sectional design. Screener questions at the beginning of the questionnaire guaranteed that respondents only answered questions in categories with which they were familiar (see also Fischer, Völckner, and Sattler 2010). The number of categories answered by a single respondent varied from one to five, with most providing answers to three categories (76.37%). Depending on the category, respondents had to imagine a situation in which they purchase a product or service, sign a contract, or choose a retailer.

I restricted the dataset to categories that were available through all waves. This led to a total of 30 categories. In addition, I eliminated respondents who did not answer all items regarding BRiC and the brand functions, were younger than 18, answered a category three times faster than the median, and displayed a uniform response style (standard deviation over all responses less than 0.20; similar to Fischer, Völckner, and Sattler 2010). Thus, the final sample resulted in 13,991 observations from 5,053 respondents.

Table 4 presents the 12 items used to measure BRiC, risk reduction, and social demonstrance exemplarily for durable and FMCG categories. To validate the proposed scales by Fischer, Völckner, and Sattler (2010), I performed an exploratory factor analysis using both Promax and Varimax rotation for the pooled dataset (see Appendix B). Both analyses yielded the same three-factor solutions (all eigenvalues are greater than 1). Each item loads higher on one factor than the other two factors. Cronbach's alpha ranges from 0.94 to 0.96, indicating good internal validity. Hence, I take the average of the respective items to construct the BRiC, risk reduction, and social demonstrance scales.

One main objective of the current research is to investigate changes in BRiC and the brand functions across waves using the scale means. For such mean comparisons, the BRiC and the brand functions scales need to be equivalent across waves (similar to the cross-country equivalence of scales, e.g., Fischer, Völckner, and Sattler 2010; Steenkamp and Baumgartner 1998). To establish measurement equivalence (invariance), I employ a multigroup confirmatory factor analysis on the three factors using robust estimation. I first test the configural invariance of the three factors. The results reveal a good model fit: $\chi^2(255) = 3500.45$, $p < 0.01$; CFI = 0.971; TLI = 0.962; SRMR = 0.024; RMSEA = 0.089. In addition, all factor loadings are large (exceeding 0.7) and significant and display a similar pattern across waves, indicating configural invariance. Next, I proceed to test metric invariance by setting the loadings to be equal across waves. Although, due to the large sample size (13,991 observations), the chi-square difference is significant, metric invariance can still be supported. The results indicate an overall good model fit: $\chi^2(291) = 3917.53$, $p < 0.01$; CFI = 0.969; TLI = 0.965; SRMR = 0.032; RMSEA = 0.086. The decrease in CFI is -0.002, which is below the recommended threshold of 0.01

(Cheung and Rensvold 2002). Finally, scalar invariance can also be established by estimating a model that sets the loadings and intercepts to be equal across waves. Model fit decreases but is still acceptable ($\chi^2(327) = 5349.20$, $p < 0.01$; CFI = 0.960; TLI = 0.959; SRMR = 0.037; RMSEA = 0.093). The decline in CFI is below 0.01 (ΔCFI = -0.009; Cheung and Rensvold 2002). Consequently, measurement equivalence is given for the BRiC, risk reduction, and social demonstrance scales, making comparisons across waves meaningful.

4.1.2 Dynamic category-level factors

To construct the dynamic category-level variables, I obtained data from the market research company YouGov, which has been extensively used in previous marketing literature (e.g., Luo, Raithel, and Wiles 2013; Stäbler and Fischer 2020). In Germany, YouGov monitors 1,326 brands, collecting data from over 2,500 respondents each day (as of July 2020). Three broad sets of metrics are tracked: media and communications metrics, purchase funnel metrics, and brand perception metrics. This research focuses on brand buzz (single-item media and communications metric) and overall brand strength (YouGov's BrandIndex measure). Brand buzz describes the proportion of respondents who have heard something positive or negative about the brand in the last two weeks. Brand strength is a multidimensional index consisting of the average of six dimensions: general impression, quality, value, satisfaction, reputation, and recommendation. Both metrics range from -100 to +100 (see Appendix C for more details).

To match the YouGov data with the BRiC categories, a matching method at the brand level was applied. Three coders independently coded all of the 1,326 brands monitored by YouGov in Germany to the 30 BRiC categories. The intercoder agreement exceeded 98%, and disagreements were resolved through discussions. In total, 28 of the BRiC categories could be replicated with YouGov brand matches, resulting in a total set of 456 brands (393 unique brands)[3]. On average, each category consists of 16 brands, with a minimum of 3 brands for drug

[3] As some brands are included in more than one category, the number of unique brands is 393.

stores and a maximum of 54 brands for mail-order companies (see Appendix C for details). To construct the category-level variables, I downloaded the daily values for all brands in each category and aggregated them to the yearly level for each brand. Average brand strength is calculated as the mean brand strength of all brands in a category for a given year. Brand strength variation is operationalized as the standard deviation of the brand strength of all brands in the category. The power of the category leader is defined as the distance between the strongest brand in the category and the second-strongest brand. Following previous research, negative publicity is operationalized as the reverse coding of the brand buzz metric (Stäbler and Fischer 2020). The number of brands in the category for each wave is equal to the number of brands tracked by YouGov in each category and wave as categorized by the coders (see van Ewijk, Gijsbrecht, and Steenkamp 2022 for a similar procedure).

I acknowledge that the brand population in YouGov represents only an approximation of the total number of brands that exist in the market for a specific category. However, utilizing the YouGov dataset as a starting point can be justified for three reasons. First, YouGov's brand population has already served as a basis for analysis in prior research in different contexts, including the examination of media coverage related to corporate social irresponsibility (Stäbler and Fischer 2020), short seller activities (Malshe, Colicev, and Mittal 2020), and investor attention (Borah et al. 2022). Second, consumers are typically aware of only a subset of brands in the market (awareness set) and consider an even smaller set of brands for purchase (consideration set; Crowley and Williams 1991). As YouGov is more likely to track brands with higher sales (Malshe, Colicev, and Mittal 2020), the probability that all brands within the awareness and consideration sets of an average consumer are included in YouGov is very high. Finally, I validate the use of YouGov's brand population as the basis for analysis by leveraging the capabilities of the large language model ChatGPT-3.5 (version April 2024) to identify three brands in Germany that operate in each category (see, e.g., Sklenarz et al. 2024 for similar uses of ChatGPT-3.5)[4]. The results support the use of the YouGov brand population as the basis of analysis. Over 82% of the brands mentioned by ChatGPT-3.5 are included in YouGov, while the missing brands primarily pertain to four categories (see Appendix C for details). As robustness checks excluding these critical four categories yield similar results (see Table A15 in Appendix E), I include all categories in the main analyses.

4.1.3 Macro-level factors

To account for the effects of the business cycle, I obtained data on yearly GDP rates expressed in season-adjusted constant prices from the German Federal Statistical Office. To separate the long-term upward trend and seasonal effects from business cycle fluctuations (Dekimpe and Deleersnyder 2018), I follow the prevalent practice in the marketing literature (e.g., Steenkamp and Fang 2011) and utilize the Hodrick-Prescott (Hodrick and Prescott 1997) low-pass filter (hereinafter HP filter), which is commonly used for yearly data (Lamey et al. 2007; Steenkamp and Fang 2011). The HP filter decomposes the log-transformed GDP data into a trend and a cyclical component by fitting a smooth curve. Following Baxter and King (1999), I set the smoothing factor λ equal to ten. The cyclical component, which is obtained by subtracting the long-term trend from the log-transformed GDP data, constitutes the final macro-level variable.

4.1.4 Control variables

Previous research has emphasized that static category variables, which do not change over time, also affect BRiC (Fischer, Völckner, and Sattler 2010). To comprise the static category variables, I collected data from a panel of 31 marketing experts in academia regarding the 30 BRiC categories. Respondents answered single-item questions regarding the visibility of consumption, the ability to judge product quality ex-ante, decision involvement, and the extent

[4] I asked ChatGPT-3.5 to name the top three brands because there are only three major drugstore brands in Germany.

of group decision-making within the category. Although all raters possess sufficient marketing expertise to rate the categories along the respective items, ratings from multiple raters can still be biased because of incorrect individual assessments. To correct this bias, I apply a confidence-based weighting procedure when averaging the responses for each category (van Bruggen, Lilien, and Kacker 2002). Similar to Fischer, Völckner, and Sattler (2010), I use raters' self-assessed confidence in their answers to construct weights for the individual responses[5]. Finally, a time trend variable is included to account for gradually changing unobserved effects.

Table 4 provides an overview of the operationalization of all variables.

4.1.5 Final dataset

All datasets are merged on the individual level to construct the final dataset for modeling. As YouGov started tracking brands in 2008, the final dataset only contains the waves 2010, 2013, 2016, and 2019. To ensure temporal separation and circumvent reversed causality, the dynamic category-level and macro-level variables are lagged by one year relative to the BRiC survey data (see Rajavi, Kushwaha, and Steenkamp 2019 for a similar procedure). As not all BRiC categories can be replicated with YouGov and because data collection for different categories can start at different points in time, the final dataset for modeling is imbalanced, consisting of 8,799 observations, 3,785 respondents, and 28 categories**.**

[5] Weights are calculated as follows: $weight_i = \frac{confidence_i}{\sum_{i=1}^{i=31} confidence_i}$, with *i* representing respondents.

Table 4: Operationalization of Variables

Variables	Operationalization	Source
Brand relevance in category [BRiC]	Average of the following four items (7-point scale) of respondent *i* in wave *w* ($\alpha = 0.94$): 1. *When I purchase a product in the given category, the brand plays –compared to other things– an important role.* [a, b] 2. *When purchasing, I focus mainly on the brand.* [a, b] 3. *To me, it is important to purchase a brand name product.*[a, b] 4. *The brand plays a significant role as to how satisfied I am with the product.* [a, b]	Secondary data from external market research provider following Fischer, Völckner, and Sattler (2010)
Risk reduction [RISK]	Average of the following four items (7-point scale) of respondent *i* in wave *w* ($\alpha = 0.96$): 1. *I purchase mainly brand name products because that reduces the risk of aggravation later.* [a, b] 2. *I purchase brand name products because I know that I get good quality.* [a, b] 3. *I choose brand name products to avoid disappointments.* [a, b] 4. *I purchase brand name products because I know that the performance promised is worth its money.* [a, b]	Secondary data from external market research provider following Fischer, Völckner, and Sattler (2010)
Social demonstrance [DEMO]	Average of the following four items (7-point scale) of respondent *i* in wave *w* ($\alpha = 0.95$): 1. *To me, the brand is indeed important because I believe that other people judge me on the basis of it.* [a, b] 2. *I purchase particular brands because I know that other people notice them.* [a, b] 3. *I purchase particular brands because I have much in common with other buyers of that brand.* [a, b] 4. *I pay attention to the brand because its buyers are just like me.* [a, b]	Secondary data from external market research provider following Fischer, Völckner, and Sattler (2010)
Age [AGE]	Age of respondent *i*.	Secondary data from external market research provider
Gender [GENDER]	Gender of respondent *i*. If female equal to 1, otherwise equal to 0.	Secondary data from external market research provider
Education [EDUCATION]	Education of respondent *i*. Equal to 1 if university degree or higher, otherwise equal to 0.	Secondary data from external market research provider
Brand strength average [BSAVE]	Brand strength corresponds to YouGov's BrandIndex measures along six dimensions and ranges from -100 to +100. Brand strength average in a category *c* represents the average of yearly BrandIndex values of all brands in category *c* in year *w-1*.	Secondary data from YouGov
Brand strength variation [BSVAR]	Brand strength corresponds to YouGov's BrandIndex measures along six dimensions and ranges from -100 to +100. The brand strength variation in a category *c* consists of the standard deviation of all brand-level yearly BrandIndex values in category *c* in year *w-1*.	Secondary data from YouGov
Power of category leader [POWER]	The power of the category leader in category *c* is calculated as the difference between the highest yearly BrandIndex value in category *c* in year *w-1* to the second-highest value.	Secondary data from YouGov

Table 4: Operationalization of Variables (Continued)

Variables	Operationalization	Source
Number of brands [NUMBER]	Number of brands in category *c* constitutes of the number of brands tracked by YouGov in category *c* in year *w-1* as categorized by the coders.	Secondary data from YouGov
Negative publicity [NEGPUB]	Negative publicity corresponds to reverse-coded buzz metric of YouGov that ranges from -100 to +100. Brand buzz in the category *c* in year *w-1* is calculated as the average yearly brand buzz values of all brands in category *c* in year *w-1*. This value is multiplied with -1 to get negative publicity [c].	Secondary data from YouGov
Business cycle [MACRO]	Cyclical component of the log-transformed GDP data using the HP filter in year *w-1*.	German Federal Statistical Office
Visibility of consumption [STATPROD$_1$]	Single item (5-point scale) measuring the visibility of consumption in a category *c*. *Consumers feel competent to objectively assess the relevant quality criteria before making their first purchase of a product, their first use of a service, or their first visit to a retail outlet in the following categories.* [b]	Secondary data from expert survey based on Fischer, Völckner, and Sattler (2010)
Ability to judge quality ex ante [STATPROD$_2$]	Single item (5-point scale) measuring the ability to judge the quality of a product or service before purchase in a category *c*. *The consumption of products/services or the visit to retail outlets in the following categories is highly visible to the public, i.e., other people notice the use of the brand/provider.* [b]	Secondary data from expert survey based on Fischer, Völckner, and Sattler (2010)
Decision Involvement [STATPROD$_3$]	Single item (5-point scale) measuring the extent of decision involvement in a category *c*. *Please imagine a typical situation in which consumers in the following categories purchase products, use a service, or visit a retail outlet.* [b] *- Consumers make their choice practically automatically.* [b] *- Consumers choose from a small set of familiar alternatives.* [b] *- Consumers look for other alternatives in addition to those they already know or that are offered to them.* [b] *- Consumers invest a lot of time to evaluate and compare all available alternatives.* [b] *- Consumers take a lot of time to evaluate and compare alternatives. A decision is only made when consumers feel that they have collected and processed all information required for the decision.* [b]	Secondary data from expert survey based on Fischer, Völckner, and Sattler (2010)
Group decision-making [STATPROD$_4$]	Single item (5-point scale) measuring the extent to which the decision-making in a category *c* occurs in a group. *The typical decision-making process in the following categories can be described as follows:* [b] *- Decision made alone* [b] *- Decision made together with other people.* [b]	Secondary data from expert survey based on Fischer, Völckner, and Sattler (2010)
Time trend [TIME]	A time trend variable accounting for gradually changing unobserved effects.	–

Notes: [a] Items are exemplarily for durables and FMCG and slightly change for services and retail. [b] Items are translated from German to English. [c] As the mean is a linear-additive operator, transforming the mean is sufficient for reverse-coding brand buzz into negative publicity.

4.2 Model Specification

In addition to comparing the mean BRiC values across waves, another main objective of this research is to investigate conditions that strengthen or weaken the relationship between the brand functions risk reduction and social demonstrance and BRiC. To do so, I consider a broad range of moderating factors on three levels: consumer, category, and macro level. On the consumer level, age (AGE), gender (GENDER), and education (EDUCATION) serve as possible moderators in the model. On the category level, average brand strength in category (BSAVE), brand strength variation in category (BSVAR), power of category leader (POWER), number of brands in category (NUMBER), and negative publicity in the category (NEGPUB) are included in the model as possible moderators. Finally, the business cycle (MACRO) enters the model at the macro level. To facilitate model convergence, I follow past research (Rajavi, Kushwaha, and Steenkamp 2019) and use grand-mean centering for category-level and macro-level variables and within-group centering (within waves) for consumer-level variables[6]. The cross-classified multilevel model that accounts for repeated observations for each respondent and the fact that each category is evaluated by multiple respondents can be written as follows (similar to Klein et al. 2019):

$$\begin{aligned} BRiC_{icw} = {} & \alpha_0 + \alpha_i^{respondent} + \alpha_c^{category} \\ & + \left(\beta_0 + \beta_i^{respondent} + \beta_c^{category}\right) \times RISK_{icw} \\ & + \left(\gamma_0 + \gamma_i^{respondent} + \gamma_c^{category}\right) \times DEMO_{icw} \\ & + \sum_{p=1}^{P=4} \delta_p STATPROD_{pc} + \delta_5 TIME_w + \varepsilon_{icw}. \end{aligned} \tag{1}$$

$$\alpha_i^{respondent} = \alpha_1 AGE_i + \alpha_2 GENDER_i + \alpha_3 EDUCATION_i + \iota_{0i}. \tag{2}$$

$$\alpha_c^{category} = \upsilon_{0c}. \tag{3}$$

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[6] Using within-wave mean-centering for consumer-level variables has the advantage that establishing scalar invariance for risk reduction and social demonstrance is not necessarily required (Rajavi, Kushwaha, and Steenkamp 2019). I do not standardize the predictor variables, which might be problematic in multilevel models where the variance is partitioned across different levels (Steenkamp and Geyskens 2006).

$$\alpha_0 = \alpha_{00} + \alpha_4 BSAVE_{cw} + \alpha_5 BSVA_{cw} + \alpha_6 POWER_{cw} + \alpha_7 NUMBER_{cw} + \alpha_8 NEGPUB_{cw} + \alpha_9 MACRO_w. \tag{4}$$

Equation 1 relates BRiC for respondent i in category c and wave w to risk reduction ($RISK_{icw}$), social demonstrance ($DEMO_{icw}$), the consumer-level, dynamic category-level, and macro-level factors, their interactions with the brand functions, the static category control variables, a time trend variable, and an idiosyncratic error ε_{icw} that is normally distributed with zero mean and variance σ_ε^2. To consider repeated observations per respondent, because each respondent i generally evaluated more than one category, and to account for the fact that each category c is evaluated by multiple respondents, the intercept depends on respondent i and category c (Equations 2 and 3)[7]. The respondent-level random intercept $\alpha_i^{respondent}$ in Equation 2 comprises the consumer-level factors that differ across respondents i and a respondent-specific error term $\iota_{0i} \sim N\,(0, \sigma_\iota^2\,)$ to capture respondent heterogeneity. The category-level random intercept $\alpha_c^{category}$ in Equation 3 includes a category-specific error term $\upsilon_{0c} \sim N\,(0, \sigma_\upsilon^2\,)$ that accounts for heterogeneity at the category level. As respondents are randomly assigned to categories, the respondent- and category-specific errors are nonnested and independent. Respondents are different in each wave w. Equation 4 relates BRiC to the dynamic category-level factors that vary across categories c and waves w and the macro-level factor that varies only across waves w.

Equation 1 additionally includes respondent-specific ($\beta_i^{respondent}$) and category-specific ($\beta_c^{category}$) random slopes to account for the variation in the effects of risk reduction across respondents and categories. Again $\beta_i^{respondent}$ includes both the consumer-level factors and an error term $\iota_{\beta i}$ that accounts for unobserved respondent-specific heterogeneity (Equation 5). The

[7] Because the model dataset only comprises four waves, specifying a random effect for waves impedes the model's convergence. Therefore, I include time as a fixed time trend variable in the model.

category-specific random slope $\beta_c^{category}$ includes only the error term $\upsilon_{\beta c}$ controlling for category-level heterogeneity (Equation 6). Equation 7 contains the dynamic category-level factors and the macro-level factor that interact with risk reduction and represent the focus of the current research.

$$\beta_i^{respondent} = \beta_1 AGE_i + \beta_2 GENDER_i + \beta_3 EDUCATION_i + \iota_{\beta i}. \tag{5}$$

$$\beta_c^{category} = \upsilon_{\beta c}. \tag{6}$$

$$\begin{aligned}\beta_0 = \beta_{00} + \beta_4 BSAVE_{cw} + \beta_5 BSVA_{cw} + \beta_6 POWER_{cw} + \beta_7 NUMBER_{cw} \\ + \beta_8 NEGPUB_{cw} + \beta_9 MACRO_w.\end{aligned} \tag{7}$$

The respondent-specific ($\gamma_i^{respondent}$) and category-specific ($\gamma_c^{category}$) random slopes for social demonstrance are defined analogously to account for the variation in the effects of social demonstrance across respondents and categories (Equations 8 and 9). Similarly, the interaction with dynamic category-level and macro-level variables is specified analogously (Equation 10).

$$\gamma_i^{respondent} = \gamma_1 AGE_i + \gamma_2 GENDER_i + \gamma_3 EDUCATION_i + \iota_{\gamma i}. \tag{8}$$

$$\gamma_c^{category} = \upsilon_{\gamma c}. \tag{9}$$

$$\begin{aligned}\gamma_0 = \gamma_{00} + \gamma_4 BSAVE_{cw} + \gamma_5 BSVA_{cw} + \gamma_6 POWER_{cw} + \gamma_7 NUMBER_{cw} \\ + \gamma_8 NEGPUB_{cw} + \gamma_9 MACRO_w.\end{aligned} \tag{10}$$

I assume that the random intercepts and slopes for respondent *i* and category *c* are correlated and come from a multivariate normal distribution with zero mean vector **o** and a variance-covariance-matrix **Σ**:

$$\begin{pmatrix} \iota_{0i} \\ \iota_{\beta_i} \\ \iota_{\gamma_i} \end{pmatrix} \sim N\,(\mathbf{o}, \mathbf{\Sigma}_i), and \tag{11}$$

$$\begin{pmatrix} \upsilon_{0c} \\ \upsilon_{\beta_c} \\ \upsilon_{\gamma_c} \end{pmatrix} \sim N\,(\mathbf{o}, \mathbf{\Sigma}_c). \tag{12}$$

Finally, Equation 1 includes static category-level control variables that only vary across categories c and a time trend accounting for gradually changing unobserved effects.

4.3 Model Estimation

I estimate all models in a fully Bayesian framework[8] using the brms package in R (Bürkner 2017), which operates in the probabilistic programming language Stan (Stan Development Team 2019). To facilitate model estimation, parameters are estimated using weakly informative priors that follow a normal or half-normal distribution [N(0, 10)]. Robustness checks with less informative priors [N(0, 100)] yield the same results but require more estimation time (see Appendix E, Table A14). For the correlation matrix decomposition of $\mathbf{\Sigma}$, I use the regularizing LKJ prior (McElreath 2020). Posterior means are obtained by sampling from the posterior distribution using the No-U-Turn Sampler (NUTS; Hoffman and Gelman 2014). I use four chains with 4,000 iterations each and set the seed randomly at 100 to facilitate the reproduction of the results.

4.4 Addressing Endogeneity

Following Germann, Ebbes, and Grewal (2015), two main sources of endogeneity might be of concern in the current research: simultaneity (reverse causality) and omitted variable bias. I address these concerns by enriching and exploiting the dataset and using different modeling approaches as robustness checks.

4.4.1 Simultaneity and reverse causality

First, one can argue that BRiC influences managerial decisions. Firms that operate in high-BRiC categories may invest more in brand-building activities because they expect higher

[8] Estimating the model in a fully Bayesian framework becomes necessary as the number of respondent-specific random effects exceeds the number of observations in the dataset. This limits the convergence of the model using other approaches. A more restricted model including respondent- and category-specific random intercepts only can also be estimated using maximum likelihood (ML) or restricted maximum likelihood (REML). However, as Fischer, Völckner, and Sattler (2010) show, the effects of risk reduction and social demonstrance vary across individuals, which makes it reasonable to include respondent-specific random slopes in the model.

returns on their investments. Similarly, BRiC could impact average brand strength and brand strength variation in a category because consumers evaluate brands in high-BRiC categories differently (e.g., more polarized) than brands in low-BRiC categories. I address these reversed causality concerns in three ways. First, following Rajavi, Kushwaha, and Steenkamp (2019), the dynamic category- and macro-level variables are lagged by one year relative to the BRiC data. This approach additionally ensures that consumers have time to react to category and macroeconomic changes. Still, managers may know or anticipate changes in BRiC and adjust brand investments accordingly one year in advance. As BRiC is a survey-based consumer measure, it is not available to firms unless they conduct market research on BRiC. Fischer, Völckner, and Sattler (2010) show that although managers can correctly recognize differences in BRiC across categories, their estimations of consumer responses on BRiC only slightly correlate with actual consumer responses (0.364, $p < 0.05$). Moreover, this research is the first to investigate changes in BRiC over time and factors affecting these changes. Therefore, managers cannot rely on previous research findings to predict BRiC and adjust brand investments accordingly in advance.

Second, the focal dynamic category variables are based on category averages that are unlikely to be intentionally influenced by a single firm. For example, to increase the average brand strength or brand strength variation in a category, it is not sufficient for a single firm to enhance its consumer brand perception through marketing activities. At the same time, the brand perceptions of all other firms in the category must remain unchanged. As firms cannot control or anticipate the activities of other firms, the intentional influence of a single firm on BRiC is limited. Similarly, the number of brands and negative publicity in the category are not under the control of a single firm. As Stäbler and Fischer (2020) demonstrate, firms only have a limited influence on the media coverage of their misconduct. The business cycle, on the other hand, is exogenous.

4.4.2 Omitted variables

Another concern might be an omitted variable bias at the individual, category, and macro levels, which could cause the predictor variables in Equation 1 to be correlated with unobserved factors of the error term and lead to biased and inconsistent estimates (Papies, Ebbes, van Heerde 2017). To mitigate this concern, I enrich the dataset with additional static category-specific control variables obtained through expert surveys. I also control for unobserved heterogeneity across categories by incorporating a category-specific random intercept and slopes in the main model. In addition, I conduct further robustness checks by estimating a model with category-fixed effects. The results remain robust and support the main model (see Appendix E, Table A12). Similarly, individual differences may influence BRiC (Fischer, Völckner, and Sattler 2010). I account for unobserved individual heterogeneity using respondent-specific random intercepts and slopes. To address the impact of omitted, gradually changing variables, a time trend variable is included in the main model. I also estimate a time-fixed effect model as a robustness check. Again, the results closely align with the main model (see Appendix E, Table A13).

While potential issues of endogeneity are addressed by enriching the data set and employing alternative modeling approaches as robustness checks, this research does not claim to establish full causality. Therefore, the examined moderating effects of consumer-, category- and macro-level variables on the relationship between the brand functions and BRiC should be interpreted as associative rather than causal.

5 Results

5.1 Model-Free Analyses

Figure 3 displays the development of BRiC, risk reduction, and social demonstrance across the 30 categories included in the full dataset based on 13,991 observations from 5,053 respondents in five waves between 2006 and 2019. Interestingly, BRiC, risk reduction, and social demonstrance appear to be relatively stable over time, with only a few categories showing significant wave-to-wave differences (see Table 5 and Appendix D). The average BRiC across categories increased only from 3.46 in 2006 to 3.68 in 2019 (~ 6.36%[9]) and from 3.26 in 2010 to 3.68 in 2019 (~ 12,88%). The decline in BRiC from 3.46 in 2006 to 3.26 in 2010 may reflect the impact of the financial crisis in 2008. During economic downturns, consumers often exhibit more frugal behavior by reallocating their spending towards non-branded products (Scholdra et al. 2022), potentially causing brands to lose relevance. Generally, out of a total of 120 potential wave-to-wave category-level changes, only 16 (13.33%) are significant when conducting pairwise t-tests with Bonferroni correction ($p < 0.05$)[10]. This model-free evidence supports the initial proposition by Fischer, Völckner, and Sattler (2010) that BRiC describes consumer predisposition and is relatively stable over time.

However, as evident in Figure 3 and Table 5, changes in BRiC and brand functions differ between categories and are significant for some categories. One of the most notable significant changes in BRiC can be observed for express delivery services (see Table 5), where BRiC increased from 2.63 in 2006 to 4.26 in 2019 (~ 62%). A possible reason for this high increase in BRiC could be attributed to the growth in e-commerce retail during the same period (Geuens 2025). Ignoring such significant changes and assuming that BRiC remains constant across all categories may result in erroneous managerial implications and missed business opportunities, given the important moderating role of BRiC in the value creation process of brands (e.g., Nguyen and Feng 2021; Rajavi, Kushwaha, and Steenkamp 2019).

Nevertheless, it might not be adequate to compare BRiC values solely at the beginning and the end of an observation period. For instance, the change in BRiC for the category of

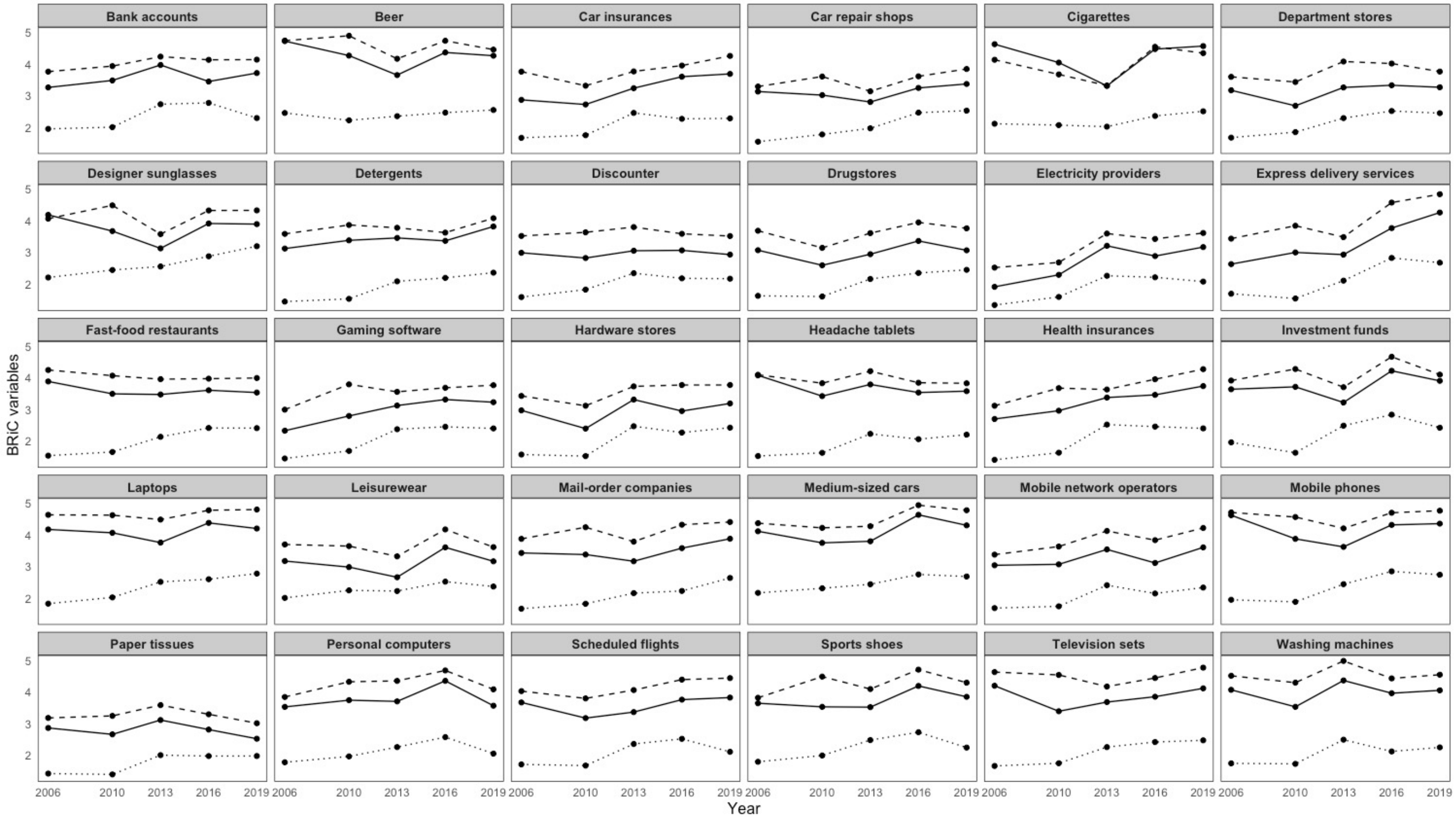
[9] Note that BRiC, risk reduction, and social demonstrance are measured on a 7-point scale.
[10] Given the large sample size, I assume normality of the sampling distribution. However, applying the nonparametric Wilcoxon rank test that does not require a normal distribution produces similar results.

leisurewear from 2006 to 2019 is nearly zero. However, there is a significant wave-to-wave change from 2.65 in 2013 to 3.60 in 2016, by almost 36%. Similarly, specific events within the category can lead to sudden changes in BRiC. A prominent example is the Volkswagen emissions scandal in 2015, which initiated negative spillover effects on the entire German automotive industry (Bachmann et al. 2023). Concurrently, a sudden significant increase in BRiC by over 22% is observed in 2016 (Table 5).

Additionally, BRiC not only exhibits changes within a category but also relative to other categories. Table A9 in the Appendix shows the rankings of the categories in each wave. Changes in rankings indicate that the category-level changes in BRiC are not solely influenced by overall trends in BRiC but also by factors pertinent to a specific category. For example, in 2016, BRiC in the medium-sized cars category not only increased in absolute terms, but the brand also became more important relative to other categories. While in 2006, medium-sized cars ranked seventh in BRiC, they reached first place in 2016. Similarly, bank accounts experienced a sudden relative increase in BRiC following the financial crisis in 2008. In 2006, bank accounts held the 16th rank, but by 2013, they had risen to the second position. However, in subsequent years, the ranking of bank accounts dropped again below 16th place.

Finally, when examining what might drive the changes in BRiC specifically, the similarity in the patterns between BRiC and risk reduction is striking (e.g., categories of medium-sized cars, drugstores, and washing machines; see Figure 3). Changes in BRiC appear to be driven strongly by the risk reduction function, which aligns with earlier findings by Fischer, Völckner, and Sattler (2010). Therefore, the question of what drives the risk-reducing function of brands seems equally important.

Figure 3: Changes in BRiC, Risk Reduction, and Social Demonstrance Over Time



Notes: The values represent the average across all respondents in each category and wave (year). BRiC is displayed in black solid line, risk reduction is depicted in black dashed line, and social demonstrance is shown in black dotted line. Number of observations = 13,991, number of individuals = 5,053, number of categories = 30.

Table 5: Means and Changes in BRiC by Category and Wave

Category	2006	2010	2013	2016	2019	Diff_06_10 (in %)	Diff_10_13 (in %)	Diff_13_16 (in %)	Diff_16_19 (in %)	Diff_06_19 (in %)
Bank accounts	3.26	3.48	3.97	3.44	3.71	6.75	14.08	-13.35	7.85	13.80
Beer	4.72	4.26	3.65	4.36	4.26	-9.75	-14.32	19.45	-2.29	-9.75
Car insurances	2.86	2.71	3.23	3.59	3.68	-5.24	19.19	11.15	2.51	28.67
Car repair shops	3.13	3.01	2.79	3.24	3.37	-3.83	-7.31	16.13	4.01	7.67
Cigarettes	4.62	4.04	3.30	4.47	4.56	-12.55	-18.32	**35.45**	2.01	-1.30
Department stores	3.16	2.67	3.25	3.32	3.26	**-15.51**	**21.72**	2.15	-1.81	3.16
Designer sunglasses	4.19	3.68	3.13	3.92	3.90	-12.17	-14.95	**25.24**	-0.51	-6.92
Detergents	3.12	3.38	3.46	3.37	3.82	8.33	2.37	-2.60	13.35	22.44
Discounter	2.99	2.82	3.05	3.07	2.93	-5.69	8.16	0.66	-4.56	-2.01
Drugstores	3.07	2.59	2.94	3.36	3.07	**-15.64**	13.51	14.29	-8.63	0.00
Electricity providers	1.91	2.29	3.21	2.89	3.17	19.90	**40.17**	-9.97	9.69	**65.97**
Express delivery services	2.63	3.00	2.93	3.77	4.26	14.07	-2.33	**28.67**	13.00	**61.98**
Fast-food restaurants	3.89	3.49	3.47	3.61	3.53	-10.28	-0.57	4.03	-2.22	-9.25
Gaming software	2.33	2.79	3.12	3.31	3.23	19.74	11.83	6.09	-2.42	**38.63**
Hardware stores	2.97	2.39	3.31	2.95	3.19	**-19.53**	**38.49**	-10.88	8.14	7.41
Headache tablets	4.08	3.42	3.79	3.53	3.58	-16.18	10.82	-6.86	1.42	-12.25
Health insurances	2.70	2.96	3.38	3.46	3.74	9.63	14.19	2.37	8.09	**38.52**
Investment funds	3.64	3.71	3.22	4.22	3.90	1.92	-13.21	**31.06**	-7.58	7.14
Laptops	4.17	4.06	3.75	4.38	4.20	-2.64	-7.64	16.80	-4.11	0.72
Leisurewear	3.17	2.98	2.65	3.60	3.16	-5.99	-11.07	**35.85**	-12.22	-0.32
Mail-order companies	3.42	3.37	3.16	3.58	3.87	-1.46	-6.23	13.29	8.10	13.16
Medium-sized cars	4.11	3.74	3.79	4.63	4.30	-9.00	1.34	**22.16**	-7.13	4.62
Mobile network operators	3.03	3.06	3.54	3.11	3.60	0.99	15.69	-12.15	15.76	18.81
Mobile phones	4.62	3.87	3.62	4.31	4.35	**-16.23**	-6.46	19.06	0.93	-5.84
Paper tissues	2.85	2.65	3.10	2.80	2.51	-7.02	16.98	-9.68	-10.36	-11.93
Personal computers	3.52	3.73	3.69	4.34	3.56	5.97	-1.07	17.62	**-17.97**	1.14
Scheduled flights	3.66	3.17	3.36	3.75	3.81	-13.39	5.99	11.61	1.60	4.10
Sports shoes	3.64	3.52	3.51	4.18	3.84	-3.30	-0.28	19.09	-8.13	5.49
Television sets	4.19	3.38	3.67	3.84	4.11	**-19.33**	8.58	4.63	7.03	-1.91
Washing machines	4.06	3.52	4.36	3.95	4.04	-13.30	**23.86**	-9.40	2.28	-0.49
Mean	3.46	3.26	3.38	3.68	3.68	-4.36	5.44	9.40	0.53	9.38

Notes: Values in bold indicate significant changes using pairwise t-tests with Bonferroni correction ($p < 0.05$). Mean values are averaged across categories.

These descriptive analyses reveal three key insights. First, overall changes in BRiC over time tend to be relatively subtle. However, following category- or macro-level events (e.g., firm or global crises), BRiC in affected categories can undergo significant changes. Second, changes in BRiC can either be permanent, as seen with express delivery services, or temporary, as exemplified by the medium-sized cars category. Finally, changes in BRiC closely align with changes in risk reduction, underlining the need to investigate factors that affect the risk-reduction function of BRiC. Here, dynamic category-level and macro-level factors such as negative publicity or the business cycle may impact the relationship between the brand functions and BRiC, ultimately influencing its overall level. To investigate this further, the results of the model-based analyses are discussed in the following (see Table A10 in Appendix D for the descriptive statistics and correlations of the model variables).

5.2 Model-Based Analyses

Table 6 reports the parameter estimates for the main effects (M1a) and interaction effects model (M1b) containing random intercepts and slopes for both respondents and categories. Both models display very good model convergence (all $\hat{R} \leq 1.004$) and model fit (Bayesian R^2 = 0.787). Statistical significance in the Bayesian framework is judged based on the posterior distribution. Coefficients in bold indicate that 90% of the posterior density, displayed in brackets, excludes zero. Note that I report the unstandardized mean-centered coefficients.

Direct effects. In line with Fischer, Völckner, and Sattler (2010), findings of the main effects model (M1a) show that risk reduction (β_{00} = 0.672) and social demonstrance (γ_{00} = 0.247) are positively associated with BRiC, whereby the effect of risk reduction is larger than that of social demonstrance. Similarly, age (α_1 = 0.003) is positively associated with BRiC. Finally, a positive trend in BRiC (δ_5= 0.177) over the observation period from 2010 to 2019 becomes evident. Interestingly, I do not find any significant associations between gender, education, category-level factors, and macro-level factors and BRiC.

Indirect effects. Model 1b shows how consumer-level, category-level, and macro-level factors influence the relationship of the brand functions with BRiC. The following findings can be reported regarding the relationship between risk reduction and BRiC. On the consumer level, the current research results partially support Fischer, Völckner, and Sattler (2010) by indicating a positive interaction of age (β_1 = 0.003). In contrast to them, I do not find a significant interaction effect of gender.

One of the main foci of this research lies in the dynamic category variables. In line with previous expectations, average brand strength in the category (β_4 = 0.005), the number of brands in the category (β_7 = 0.002), and negative publicity (β_8 = 0.011) strengthen the association between risk reduction and BRiC. However, I do not find any significant interaction effect of brand strength variation, the power of the category leader, and the business cycle on the relationship between risk reduction and BRiC. For instance, if many new brands enter the car category, it increases the importance of brands to reduce purchasing risk in the category. However, greater variance among brands in the category does not have a significant effect.

Regarding the relationship between social demonstrance and BRiC, the results show that the importance of social demonstrance decreases with age (γ_1 = -0.002) but increases in times of economic upturns (γ_9 = 0.842). Hence, in line with previous business cycle literature (e.g., Scholdra et al. 2022), brands gain in relevance for displaying status or a self-concept during economic growth. Surprisingly, I do not find any significant effect of dynamic category-level factors on the association of social demonstrance and BRiC in the main model.

Table 6: Results of the Main Models

DV: BRiC	Expected effects	M1a		M1b	
INTERCEPT		**3.024**	**[2.905, 3.140]**	**3.020**	**[2.905, 3.137]**
RISK		**0.672**	**[0.648, 0.697]**	**0.671**	**[0.644, 0.699]**
RISK x AGE				**0.003**	**[0.002, 0.004]**
RISK x GENDER				-0.004	[-0.028, 0.021]
RISK x EDUCATION				0.002	[-0.024, 0.029]
RISK x BSAVE	(+)			**0.005**	**[0.001, 0.009]**
RISK x BSVA	(+)			0.002	[-0.002, 0.006]
RISK x POWER	(+)			0.000	[-0.002, 0.003]
RISK x NUMBER	(+)			**0.002**	**[0.000, 0.004]**
RISK x NEGPUB	(+)			**0.011**	**[0.004, 0.018]**
RISK x MACRO	(+/-)			-0.034	[-0.649, 0.576]
DEMO		**0.247**	**[0.222, 0.272]**	**0.250**	**[0.219, 0.279]**
DEMO x AGE				**-0.002**	**[-0.003, -0.001]**
DEMO x GENDER				-0.018	[-0.045, 0.010]
DEMO x EDUCATION				0.010	[-0.020, 0.041]
DEMO x BSAVE	(+)			-0.001	[-0.005, 0.003]
DEMO x BSVA	(+)			-0.002	[-0.006, 0.002]
DEMO x POWER	(+)			0.000	[-0.003, 0.003]
DEMO x NUMBER	(+/-)			-0.001	[-0.003, 0.002]
DEMO x NEGPUB	(-)			-0.008	[-0.015, 0.000]
DEMO x MACRO	(+)			**0.842**	**[0.115, 1.576]**
AGE		**0.003**	**[0.002, 0.004]**	**0.005**	**[0.003, 0.006]**
GENDER		0.003	[-0.032, 0.038]	0.004	[-0.035, 0.043]
EDUCATION		-0.028	[-0.067, 0.011]	-0.027	[-0.070, 0.015]
BSAVE		0.002	[-0.006, 0.009]	0.004	[-0.003, 0.012]
BSVA		0.002	[-0.005, 0.008]	0.004	[-0.003, 0.011]
POWER		0.001	[-0.003, 0.005]	0.001	[-0.004, 0.005]
NUMBER		0.000	[-0.003, 0.003]	0.001	[-0.002, 0.005]
NEPUB		0.008	[-0.006, 0.021]	0.013	[-0.001, 0.027]
MACRO		-0.290	[-2.134, 1.549]	-0.444	[-2.320, 1.450]
TIME		**0.177**	**[0.136, 0.218]**	**0.175**	**[0.133, 0.217]**
Category controls		yes		yes	
$\sigma_{\iota 0}$ (Respondent)		0.386	[0.361, 0.411]	0.384	[0.360, 0.409]
$\sigma_{\iota\beta}$		0.205	[0.191, 0.219]	0.202	[0.189, 0.216]
$\sigma_{\iota\gamma}$		0.205	[0.184, 0.226]	0.201	[0.179, 0.222]
$\sigma_{\upsilon 0}$ (Category)		0.129	[0.095, 0.170]	0.125	[0.093, 0.165]
$\sigma_{\upsilon\beta}$		0.065	[0.049, 0.084]	0.061	[0.045, 0.081]
$\sigma_{\upsilon\gamma}$		0.064	[0.047, 0.085]	0.062	[0.044, 0.084]
σ_{ε} (Residual)		0.819	[0.806, 0.832]	0.819	[0.806, 0.831]
Bayesian R^2		0.787		0.787	

Notes: Estimates represent posterior means and are unstandardized. The 90% posterior density intervals are indicated in brackets. Bold coefficients indicate that 90% of the posterior density excludes zero (similar to $p < 0.10$ in frequentist statistical modeling). Estimates for static category variables are omitted due to space limits. Number of observations = 8,977, number of individuals = 3,785, number of categories = 28.

5.3 *Conditional Effects*

To assess the effect sizes of the significant interaction effects, I analyze the conditional effects for low and high levels of risk reduction (Figure 4) and social demonstrance (Figure 5) at low and high levels of the dynamic category- and macro-level moderators in the main model with interactions (M1b). In the following, low versus high levels of a variable refer to one standard deviation below or above the mean. All other variables are held at their means (equal to zero for mean-centered and dummy variables) except for the time variable, which is set to one (i.e., 2010 as the base year).

Figure 4: Conditional Effects for Risk Reduction (RISK)

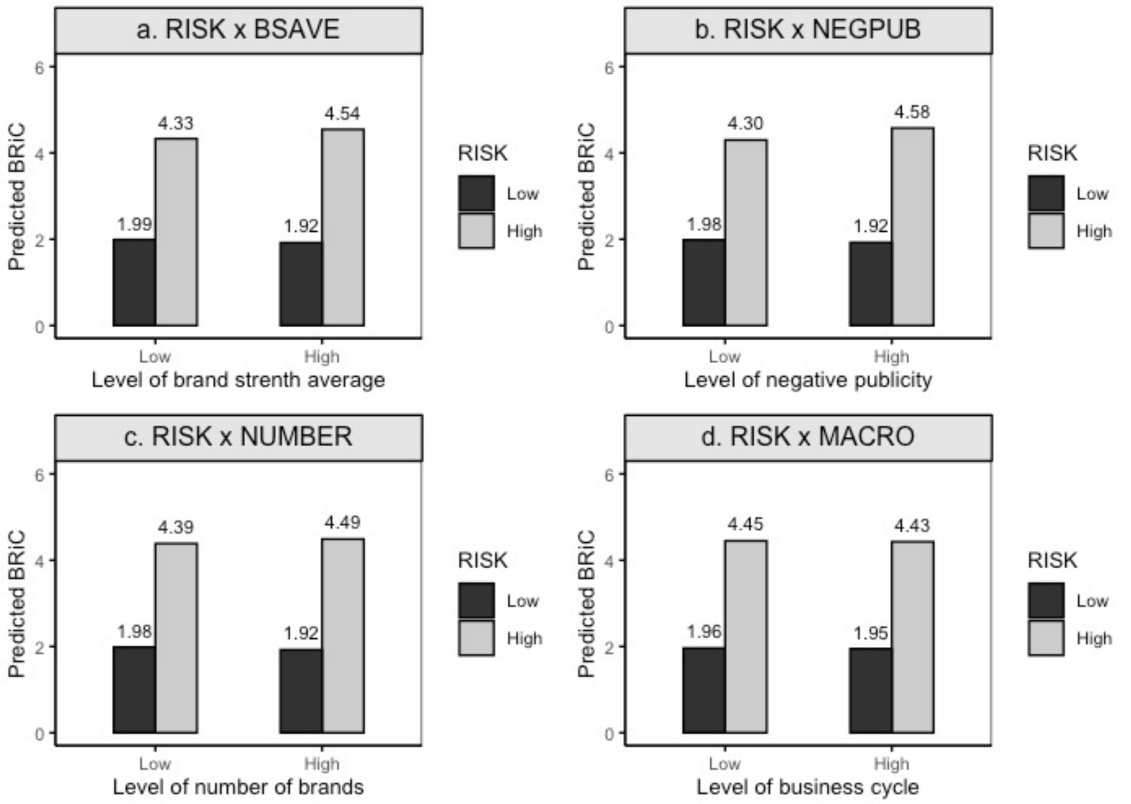
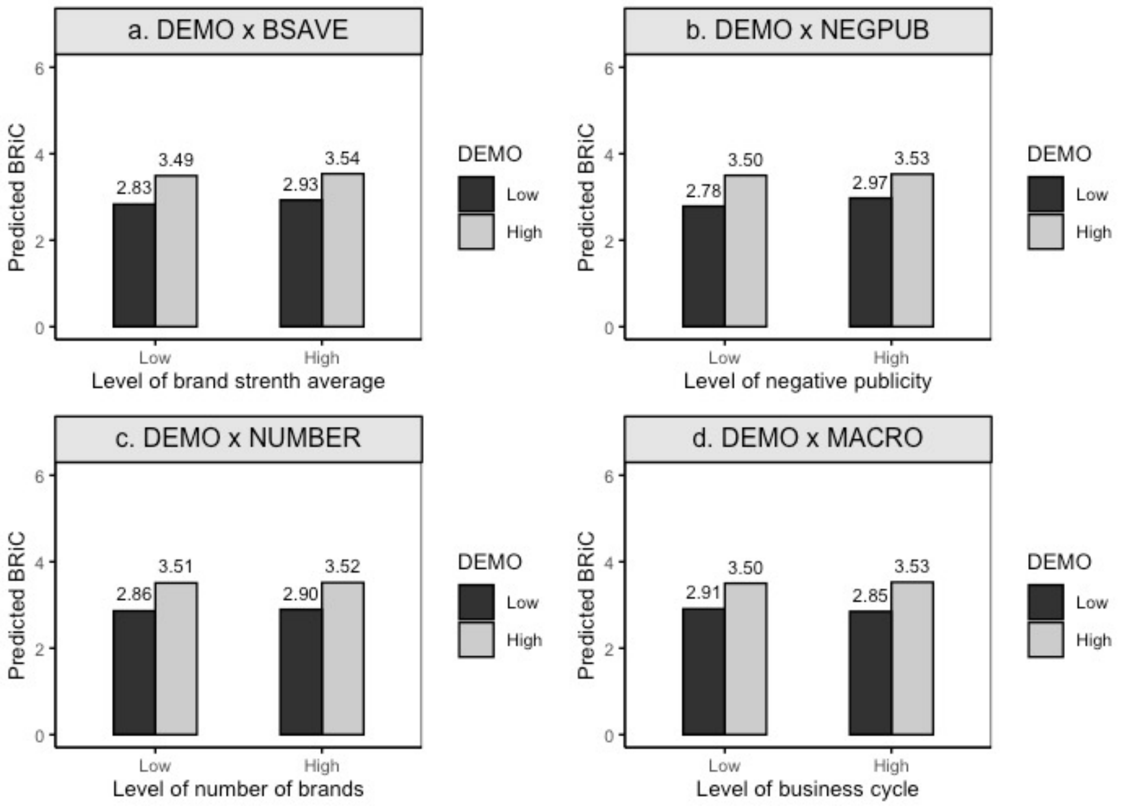


Figure 4 shows that the interaction effects of the dynamic category variables vary between low and high levels of risk reduction (RISK). While for high levels of risk reduction, an increase in the dynamic category variables increases BRiC, the opposite can be observed for low levels of risk reduction. For example, when risk reduction is high, an increase in negative publicity

(NEGPUB) in the category from low to high levels increases BRiC from 4.30 to 4.58. This increase by +0.28 [0.10; 0.46] is significant compared to a nonsignificant decrease by -0.06 [-0.18; 0.07] for low levels of risk reduction (Table 7). Similarly, when risk reduction is high, a change in brand strength average (BSAVE) from low to high levels increases BRiC significantly from 4.33 to 4.54 (Δ_{BSAVE} = 0.21 [0.01; 0.41]). When risk reduction is low, increases in the dynamic category variables from low to high levels do not lead to significant changes in BRiC. An increase from low to high levels in the business cycle (MACRO) decreases BRiC for both low and high levels of risk reduction, albeit these changes are not significant (see Table 7).

Figure 5: Conditional Effects for Social Demonstrance (DEMO)



In contrast, the pattern of conditional effects of the dynamic category variables is similar for low and high levels of social demonstrance (DEMO). For both low and high levels of social demonstrance, an increase in the dynamic category variables from low to high values increases

BRiC. However, only the conditional effect of negative publicity (NEGPUB) is significant. When social demonstrance is low, high (vs. low) levels of negative publicity in the category increase BRiC significantly by +0.19 [0.04; 0.34]. For the macro-level variable (MACRO), I find contradicting effects for low versus high levels of social demonstrance. While a shift from low to high levels in the business cycle increases BRiC for high levels of social demonstrance, the opposite can be observed for low levels of social demonstrance. However, these changes are again not significant (see Table 7).

Table 7: Changes in BRiC Conditional on Risk Reduction and Social Demonstrance

		RISK			
		Low		High	
		Change in BRiC		Change in BRiC	
BSAVE	Low-High	-0.07	[-0.21; 0.06]	**0.21**	**[0.01; 0.41]**
NEGPUB	Low-High	-0.06	[-0.18; 0.07]	**0.28**	**[0.10; 0.46]**
NUMBER	Low-High	-0.06	[-0.13; 0.01]	0.10	[-0.01; 0.22]
MACRO	Low-High	-0.02	[-0.10; 0.06]	-0.02	[-0.12; 0.07]
		DEMO			
		Low		**High**	
		Change in BRiC		**Change in BRiC**	
BSAVE	Low-High	0.10	[-0.08; 0.27]	0.05	[-0.09; 0.18]
NEGPUB	Low-High	**0.19**	**[0.04; 0.34]**	0.03	[-0.10; 0.16]
NUMBER	Low-High	0.03	[-0.06; 0.13]	0.01	[-0.06; 0.08]
MACRO	Low-High	-0.06	[-0.15; 0.03]	0.02	[-0.05; 0.10]

Notes: Low versus high levels of a variable refer to one standard deviation below or above the mean. Estimates of changes in BRiC represent posterior means. The 90% posterior density intervals are indicated in brackets. Estimates in bold indicate that 90% of the posterior density exclude zero.

The higher number of significant changes in BRiC attributed to the moderating effects of the dynamic category variables on risk reduction supports the notion that risk reduction is generally more important for BRiC than social demonstrance. Notably, the difference between the category with the lowest BRiC value (electricity providers) and the category with the highest BRiC value (beer) was 1.97 in 2010 (see Table 5). This implies that all significant changes in BRiC, resulting from an increase of dynamic category-level moderators from low to high levels, are sizable. For example, an increase in BRiC of 0.28, as observed in the case of an increase in negative publicity from low to high levels when risk reduction is high, can advance a category from rank 10 to rank 5 in 2010 (see Table A9 Appendix D).

5.4 Robustness Checks

To evaluate the robustness of the findings, I conducted several robustness checks. First, a model with random intercepts for respondents and categories, along with random slopes for respondents only, was estimated (Appendix E, Table A11). Second, I applied a category-fixed effects model (Appendix E, Table A12), excluding the static category variables, to focus on the influence of dynamic category factors by controlling for all time-invariant category effects. Similarly, I estimated a time-fixed effects model that controls for all time-variant influences, such as yearly macroeconomic changes (Appendix E, Table A13). Additionally, I re-estimated the main model (M1a and M1b) using less informative priors [N(0, 100)] to examine whether the choice of priors affected the parameter estimates (Appendix E, Table A14). Finally, I performed a robustness check excluding the categories designer sunglasses, investment funds, health insurance, and gaming software, which were identified as problematic based on the previous ChatGPT-3.5 coding process (Appendix E, Table A15). Across all models, the results demonstrate a high level of robustness (see Appendix E for details), thereby reinforcing the conclusions drawn from the main model (M1a and M1b). The only exception is the moderating effect of the business cycle, which becomes insignificant with alternative model specifications, except for the model with uninformative priors and, therefore, warrants cautious interpretation.

6 Discussion

6.1 Summary of Findings

Brand relevance in category (BRiC) can provide guidance for managers when allocating marketing budgets. Some categories, such as the car industry, require a strong focus on branding, whereas other categories, like paper tissues, demand attention to other factors such as pricing (Fischer, Völckner, and Sattler 2010). Recently, BRiC has been widely used by researchers as an important moderating variable between marketing activities, customer brand perceptions, and brand performance (e.g., Nguyen and Feng 2021; Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020). However, surprisingly, there is still a lack of understanding of whether the relevance of brands within a category changes over time. This paper is the first to provide key insights into the dynamics of BRiC.

To determine whether BRiC is a stable construct or evolves over time, I conducted extensive descriptive and empirical analyses using a unique dataset that comprises consumer responses on BRiC for 30 categories over five waves from 2006 to 2019. Descriptive analyses based on a dataset with 13,991 observations from 5,053 respondents show an average positive change across categories in BRiC from 3.26 in 2010 to 3.68 in 2019, an increase of +12.88% (Table 5). At the category level, even greater changes in BRiC can be observed, such as for express delivery services, where BRiC grew by over 60% from 2006 to 2019. Similarly, relative changes in BRiC between categories are also evident. Table A9 in the Appendix shows that the rankings of categories such as medium-sized cars, beer, or bank accounts vary highly across waves. For instance, bank accounts were ranked 16th out of the observed 30 categories in 2006. This changed following the financial crisis in 2008, when bank accounts advanced to second place in 2013. In 2016 and 2019, bank accounts dropped below rank 16 again. Although the return to pre-event levels underlines the relative stability of the BRiC construct, severe wave-to-wave changes in BRiC can also be observed.

A closer examination of the factors driving changes in BRiC reveals a high similarity in the progression of the graphs between risk reduction and BRiC (Figure 3). This assumption of the relatively higher importance of risk reduction for BRiC compared to social demonstrance is also supported by model-based analyses. Dynamic category factors such as the average brand strength, the number of brands, and negative publicity in the category further strengthen the association of risk reduction and BRiC. When risk reduction is high, high levels (vs. low levels) of dynamic category-level factors significantly increase BRiC up to 0.28 scale points. In contrast, model-based findings show no significant effects of dynamic category-level factors on the relationship of social demonstrance and BRiC. However, the importance of social demonstrance for BRiC grows during periods of economic expansion when consumers increasingly utilize brands to signal a self-image or status.

6.2 Managerial Implications

Previous research suggests that marketing managers should consider BRiC when allocating resources across categories (e.g., Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020). In high-BRiC categories, marketing activities more effectively enhance customer brand perceptions, such as customer-based brand equity (CBBE) or consumers' trust in brands (CTB). Similarly, positive brand perceptions (e.g., brand love) translate into higher profitability for high-BRiC categories compared to low-BRiC categories (Nguyen and Feng 2021). Thus, managers are well-advised to measure BRiC and incorporate it into their brand investment decisions. But how often should firms collect consumer responses on BRiC?

So far, marketing research has considered BRiC as a cross-category variable that is relatively stable over time (Fischer, Völckner, and Sattler 2010; Nguyen and Feng 2021). Consequently, it would be sufficient to collect data on BRiC once. Although the findings of this research partly support this notion, the positive trend in BRiC from 2006 to 2019 suggests that, overall, the relevance of brands in consumer decision-making has increased over the years. This increase is also reflected in the constant growth in the cumulative value of the Top 100 Global Brands by Interbrand (Interbrand 2023) and argues against recent opinions claiming the decline in the importance of brands (Binder and Hanssens 2015; WARC 2023). Failing to account for this growth in brand relevance and adjust brand investments accordingly could lead to a loss of profit for firms due to unrealized potential.

Additionally, differences across categories exist. While BRiC decreased by 14% from 2006 to 2019 in the beer category, it increased by over 60% for express delivery services (see Table 5). With expanding e-commerce sales, especially during the pandemic (Brewster 2022), additional growth in BRiC for express delivery services can be expected. Thus, firms planning to enter the express delivery services market or existing express delivery service firms planning to expand geographically should be aware of the high relevance of brands for consumers and the associated brand investment requirements. Failure to do so could result in the same fate as DHL, which was forced to abandon its U.S. domestic delivery business in 2008 due to strong competition (Fischer, Völckner, and Sattler 2010; Wilson and Baer 2008). Hence, the findings of this research can support managers further in their marketing strategy planning, especially as a prelaunch diagnostic measure when entering new markets. Before market entry, managers are advised to assess dynamic category characteristics and macroeconomic conditions in the market and plan branding activities accordingly. A high brand strength average in the category, possibly indicating the existence of strong competitors in the market, for example, increases BRiC and consequently might require higher brand-related investments to succeed.

The current research findings also emphasize that tracking changes in the overall BRiC might not be sufficient. Managers are well-advised to monitor BRiC for each category separately, especially following negative publicity concerning a specific category (e.g., the Volkswagen emission scandal). The proposed scale by Fischer, Völckner, and Sattler (2010) enables managers to collect consumer responses on BRiC at moderate market research costs. However, collecting data on BRiC for every category in which the firm operates might still be challenging for firms with a large product portfolio. To overcome this challenge, this research provides managers with the means to assess the development of BRiC and the brand functions in relation to dynamic category- and macro-level factors. For example, following increasing negative publicity in the category, brand relevance and especially its risk-reducing function gain importance. Managers can leverage this information and focus more on the brand and its ability to minimize consumer purchasing risk in their brand communications. In contrast, during periods of economic growth, projecting a self-concept and status gains significance for consumers. Here, marketing managers could emphasize the symbolic benefits of the brand in their communications.

6.3 Theoretical Implications

This research is the first to investigate the dynamics of BRiC. Thereby, it provides two contributions to the existing marketing literature. First, this research demonstrates that although BRiC is a relatively stable construct, significant changes can occur over time. Thus, BRiC cannot only be defined as a cross-category and cross-country construct but also as a dynamic variable that changes over time. However, for most categories, I do not find significant wave-to-wave changes in BRiC. In the absence of disruptive category-level or macro-level events, BRiC remains relatively stable, even over a period of more than 10 years. This lends partial support to previous marketing literature that treats BRiC as time-invariant and measures the construct once when analyzing longitudinal data (Nguyen and Feng 2021). Nevertheless, category-specific events such as negative publicity surrounding brands in a category or macroeconomic factors (e.g., global crises or the expansion of e-commerce) can lead to changes in BRiC for related categories. Hence, researchers working with longitudinal data need to be cautious when interpreting their results and consider possible changes in BRiC.

Second, by demonstrating that in addition to consumer-level factors, dynamic category-level and macro-level factors moderate the association between the two brand functions and BRiC, this research provides a deeper understanding of the construct. I propose the Accessibility-Diagnosticity framework (Feldman and Lynch 1988) as a possible underlying theory. Depending on category-level and macro-level factors, the accessibility and diagnosticity of the brand for reducing purchasing risk or displaying a self-concept vary. For example, with an increasing number of brands in the category, assessing alternatives becomes highly complex and challenging for consumers (Iyengar and Lepper 2000), resulting in higher uncertainty and perceived purchasing risk. To mitigate their risk, consumers can rely on well-known brands (Fischer, Völckner, and Sattler 2010). Consequently, the diagnosticity of the brand to reduce purchasing risk grows, i.e., the relationship between risk reduction and BRiC strengthens, leading to changes in BRiC.

6.4 Limitations and Directions for Future Research

Although this research builds on a large multi-source dataset covering 30 categories over five waves, it is not without limitations. This, in turn, opens opportunities for further research. First, the data only covers the German market. Based on the study by Fischer, Völckner, and Sattler (2010), who suggest that BRiC also varies across countries, it would be worthwhile to investigate the development of BRiC over time in other countries as well. Second, lab or online experiments can be applied to explore a causal relationship between the analyzed variables and BRiC or test underlying mechanisms. The latter would be of great interest in validating the proposed mechanisms based on the Accessibility-Diagnosticity Theory (Feldman and Lynch 1988). Third, it would also be interesting to analyze the effects of digitalization on brand relevance in different categories (Sklenarz et al. 2024). As mentioned before, the data reveal a steep increase in BRiC for express delivery services. Given the expansion in e-commerce over the past years (Brewster 2022), further research could analyze the effect of such market developments on BRiC in related categories. Lastly, it would be interesting to explore spillover effects between categories. The dataset hints that, for example, BRiC across the categories of cigarettes and beer might be correlated (see Figure 3). The reasons behind this association could be explored in future research.

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Appendix Paper 1

In this Appendix, I provide the following information:

1) Appendix A: The Moderator Selection Process
2) Appendix B: Factor Analyses Results
3) Appendix C: Details on the YouGov Data and Coding
4) Appendix D: Additional Descriptive Statistics
5) Appendix E: Robustness Checks

Appendix A: The Moderator Selection Process

Table A1: The Moderator Selection Process

Step 1: Identifying potential moderators		**Step 2: Assessment of the time-variance of selected moderators**	**Step 3: Evaluating the replicability and measurability of selected moderators**
BRiC literature Fischer et al. (2010)	**Brand functions:** • Risk reduction • Social demonstrance **Consumer-level factors:** • Age • Gender **Category-level factors:** • Degree of homogeneity of functional benefits • Frequency of new product introductions • Number of brands available • Visibility of consumption • Ability to judge quality ex-ante • Decision involvement • Extent of group decision-making	**Time-variant:** • Macroeconomic fluctuations • Average brand strength • Power of brand leader • Degree of homogeneity of functional benefits • Frequency of new product introductions • Number of brands available • Product-harm crises **Time-invariant:** • Risk reduction[a,b] • Social demonstrance[a,b] • Age[b] • Gender[b] • Education[b] • Visibility of consumption • Ability to judge quality ex-ante • Decision involvement • Extent of group decision-making	**Excluded variables:** • Frequency of new product introductions is excluded due to difficulties in replication of previous years. <u>**Final selection of variables**</u> **Brand functions:** • Risk reduction • Social demonstrance **Consumer-level factors:** • Age • Gender • Education **Time-variant category-level factors:** • Average brand strength • Variation in brand strength • Power of category leader • Number of brands available • Negative publicity **Macro-level factors:** • Macroeconomic fluctuations **Time-invariant category-level factors:** • Visibility of consumption • Ability to judge quality ex-ante • Decision involvement • Extent of group decision-making
Other academic literature (e.g., Beck, Rahinel, and Bleier 2020; Erdem and Swait 1998; Klein et al. 2019; Scholdra et al. 2022; Zhao, Zhao, and Helsen 2011)	**Consumer-level factors:** • Education **Category-level factors:** • Brand strength • Power of brand leader • Product-harm crises **Macro-level factors:** • Macroeconomic fluctuations		

Notes: [a] Brand functions are measured at the consumer level. [b] Consumer-level factors are time-invariant as respondents are different in each wave of data collection.

Appendix B: Factor Analyses Results

The following presents the factor analyses of the BRiC, risk reduction, and social demonstrance items using both Promax and Varimax rotation for the pooled dataset. In both cases, the factor analyses yield a three-factor solution with all eigenvalues greater than one. Each item loads higher on one of the factors than the others. This confirms the proposed scales by Fischer, Völckner, and Sattler (2010). As Cronbach's alpha for the pooled dataset ranges from 0.94 to 0.96, indicating good internal validity, I take the average of the respective items to construct the BRiC, risk reduction, and social demonstrance scales.

Table A2: Factor Analysis for the Pooled Data Using Promax Rotation

	Social demonstrance	**Risk reduction**	**BRiC**
	Factor 1	Factor 2	Factor 3
	(3.344)	(3.334)	(2.581)
BRiC Item 1			**0.880***
BRiC Item 2			**0.925***
BRiC Item 3		0.249	**0.697***
BRiC Item 4	0.126	0.113	**0.676***
Risk Item 1		**0.912***	
Risk Item 2		**0.903***	
Risk Item 3		**0.923***	
Risk Item 4		**0.869***	
Demo Item 1	**0.897***		
Demo Item 2	**0.916***		
Demo Item 3	**0.924***		
Demo Item 4	**0.909***		

Notes: Eigenvalues (greater than 1) for each factor are reported in parenthesis below the factor. All values are across categories. *Indicates the highest loading.

Table A3: Factor Analysis for the Pooled Data Using Varimax Rotation

	Risk reduction	**Social demonstrance**	**BRiC**
	Factor 1	Factor 2	Factor 3
	(3.836)	(3.481)	(2.633)
BRiC Item 1	0.457	0.218	**0.751***
BRiC Item 2	0.443	0.230	**0.776***
BRiC Item 3	0.551	0.213	**0.668***
BRiC Item 4	0.446	0.327	**0.632***
Risk Item 1	**0.843***	0.188	0.350
Risk Item 2	**0.842***	0.181	0.361
Risk Item 3	**0.851***	0.200	0.348
Risk Item 4	**0.820***	0.214	0.358
Demo Item 1	0.150	**0.863***	0.177
Demo Item 2	0.179	**0.879***	0.161
Demo Item 3	0.176	**0.887***	0.164
Demo Item 4	0.161	**0.878***	0.189

Notes: Eigenvalues (greater than 1) for each factor are reported in parenthesis below the factor. All values are across categories. *Indicates the highest loading.

Appendix C: Details on the YouGov Data and Coding

Data source. The dynamic category variables are obtained from YouGov, a global market research company. For the German market, the company maintains a daily online panel of over 2,500 consumers monitoring over 1,300 brands from 37 different industry sectors (status July 2020) and thus offers representative measures that have been used in prior research in various settings (e.g., Luo, Raithel, and Wiles 2013; Stäbler and Fischer 2020).

YouGov collects data on different measures that reflect the consumer purchase funnel. In this study, I focus on two measures: brand buzz and brand strength. Brand buzz reflects the number of respondents who have heard anything negative or positive about a brand over the past two weeks (see Table A4 for the exact questions). It ranges from -100 to +100 and is calculated by subtracting the percentage of negative responses from the percentage of positive responses. As positive values represent positive buzz, I reverse code the buzz metric to obtain the negative publicity variable by multiplying the average brand buzz in the category by -1 (Stäbler and Fischer 2020).

Brand strength is a multidimensional index comprising six dimensions: general impression, quality, value, satisfaction, reputation, and recommendation. For each dimension, respondents indicate the brands that they either categorize as positive or negative. For example, for general impression, respondents select all the brands they agree with the positive statement (Which of the following brands do you have a generally *positive* feeling about?) and with the negative statement (Which of the following brands do you have a generally *negative* feeling about?). Similar to the buzz metric, the general impression score ranges from -100 to +100 and is calculated by subtracting the percentages of negative responses from the percentage of positive responses.

Variable operationalization. To construct the dynamic category-level measures, I downloaded the daily values for all brands in each category and aggregated them to yearly values for each brand. If a brand is tracked twice in YouGov (e.g., in different sectors), I download both values and use their mean. Average brand strength in the category is calculated as the mean brand strength value of all brands in the category for each year, and brand strength variation is the standard deviation of the brand strength values of all brands in the category. The power of the category leader is operationalized as the distance of the strongest brand in the category to the second strongest brand. The number of brands in the category is equal to the number of brands tracked by YouGov in each category and year (see also van Ewijk, Gijsbrecht, and Steenkamp 2022 for a similar approach).

Table A4: Questions Used by YouGov

YouGov metrics	Questions
Buzz	Over the past two weeks, which of the following brands have you heard something *positive/negative* about (whether in the news, through advertising, or talking to friends and family)?
Impression	Which of the following brands do you have a generally *positive/negative* feeling about?
Satisfaction	Which of the following brands would you say that you are a *satisfied/dissatisfied* customer of?
Quality	Which of the following brands do you think represents *good/poor* quality?
Reputation	Imagine you were looking for a job (or advising a friend looking for a job). Which of the following companies would you be *proud/embarrassed* to work for?
Value	Which of the following brands do you think *represents good/poor value for money*?
Recommendation	Which of the following brands would you *recommend*/tell a friend to *avoid*?

Coding of YouGov brands into BRiC categories. As all YouGov measures are at the brand level, brands must be categorized into the BRiC categories before calculating the category-level variables. Therefore, three coders (including the author) independently coded all 1,326 brands monitored by YouGov in Germany in 2020 to the 30 BRiC categories. Overall, the intercoder agreement was over 98%. Brands that were categorized into a specific category by all three coders were assigned class A, and brands that were only categorized by two coders were class B. Brands that were only categorized by one coder were classified as class C. In the first step, all class A brands were allocated to the respective categories. In the next step, disagreements in class B and class C brands were resolved through discussions. This led to a final selection of 456 brands (393 unique brands), with a minimum of three brands for drug stores and a maximum of 54 brands for mail-order companies ($M = 16.29$, $SD = 12.21$). In total, 28 of the BRiC categories could be replicated with YouGov brand matches (see Table A5).

Verification of the YouGov brand population. To verify the use of YouGov's brand population as a starting point, the large language model ChatGPT-3.5 (version April 2024) was used. Following past research using ChatGPT-3.5 for similar purposes (Sklenarz et al. 2024), I used two different prompts to reduce the answers' sensitivity towards the formulation of the prompt. First, I instructed ChatGPT-3.5 to identify as a highly intelligent question-answering bot and asked to name three familiar brands that operate in each of the 30 BRiC categories. In the second scenario, ChatGPT-3.5 was instructed to act as an average German consumer and answer the same question. Since the answers should be based on the German market, both questions were asked in German. Table A6 presents the prompts in German along with their English translations. In the first case, 83% of the brands mentioned by ChatGPT-3.5 were included in the YouGov sample. In the second case, this number amounted to 82%. The brands missing in the YouGov sample mostly center around the four categories designer sunglasses, investment funds, health insurance, and gaming software. As the results remain unchanged when excluding these problematic categories (see Table A14 in Appendix E), I included all 28 categories in the main analyses.

Table A5: Number of Brands in Each BRiC Category

Category	Number of brands
Bank accounts	17
Beer	28
Car insurances	28
Car repair shops	6
Department stores	7[a]
Designer sunglasses	6
Detergent	24
Discounter	9
Drug stores	3
Electricity providers	18
Express delivery services	11
Fast-food restaurants	11
Gaming software	5
Hardware stores	7
Headache tablets	6
Health insurances	20
Investment funds	5
Laptops	14
Leisurewear	48
Mail-order companies	54
Medium-sized cars	23
Mobile network operators	18
Mobile phones	18
Personal computers	8
Scheduled flights	18
Sport shoes	10
Television sets	12
Washing machines	22
Total	456
Mean	16.29
SD	12.21

Notes: At the time of data collection, department stores included 7 brands. However, in previous years, one department store brand, which is a merger of two department stores was tracked as two separate brands. Thus, the number of brands in department stores category can vary across years.

Table A6: Prompts to ChatGPT-3.5

Prompt	German: Du bist ein hochintelligenter Fragen beantwortender Bot. Wenn ich dir eine Frage stelle, die auf der Wahrheit beruht, wirst du mir die Antwort geben. English: You are a highly intelligent question-answering bot. If I ask you a question based on the truth, you will give me the answer.
Response by ChatGPT-3.5	*German:* *Ja, ich werde mein Bestes tun, um deine Frage basierend auf verfügbaren Informationen wahrheitsgemäß zu beantworten. Was möchtest du wissen?* *English:* *Yes, I will do my best to answer your question truthfully based on the available information. What would you like to know?*
Prompt	German: Bitte gebe nun für jede der unten aufgeführten Kategorien drei dir bekannte Marken/Anbieter an, die in der jeweiligen Kategorie tätig sind. Schreibe alle Namen ausschließlich in Kleinbuchstaben (z.B. mustermann statt Mustermann). Autowerkstätten Bankkonten Baumärkte Bier Designer-Sonnerbrillen Discounter Drogerien Expresszustelldienste Fast Food Restaurants Fernseher Freizeitbekleidung Handys Investmentfonds Kaufhäuser Kfz-Versicherungen Kopfschmerzmittel Krankenversicherungen Laptops Linienflüge für Privatreisen Mittelklassewagen Mobilfunkbetreiber Papiertaschentücher PCs/Computer Spielesoftware Sportschuhe Strom Versandhändler Waschmaschinen Waschmittel Zigaretten English: Please provide three known brands/providers for each of the categories listed below. Write all names exclusively in lowercase (e.g., mustermann instead of Mustermann). Car repair shops Bank accounts

Hardware stores
Beer
Designer sunglasses
Discounters
Drugstores
Express delivery services
Fast-food restaurants
Television sets
Leisurewear
Mobile phones
Investment funds
Department stores
Car insurance
Headache tablets
Health insurance
Laptops
Scheduled flights
Medium-sized cars
Mobile network operators
Paper tissues
PCs/Computers
Gaming software
Sports shoes
Electricity providers
Mail-order companies
Washing machines
Detergents
Cigarettes

Response by ChatGPT-3.5	*The answer provided by ChatGPT-3.5 is not disclosed for confidentiality reasons to not reveal the brands provided by YouGov. Details are available on request.*
Prompt	German: Nehme nun an, dass du ein normaler deutscher Verbraucher bist. Beantworte die folgende Frage wahrheitsgemäß, indem du diese Rolle annehmen. English: Now assume you're an average German consumer. Answer the following question truthfully, taking on this role.
Response by ChatGPT-3.5	*German:* *Natürlich, ich kann mir vorstellen, wie ein durchschnittlicher deutscher Verbraucher denken würde. Bitte stelle deine Frage.* *English:* *Of course, I can imagine how an average German consumer would think. Please ask your question.*

Prompt

German:
Bitte gebe nun für jede der unten aufgeführten Kategorien drei dir bekannte Marken/Anbieter an, die in der jeweiligen Kategorie tätig sind. Schreibe alle Namen ausschließlich in Kleinbuchstaben (z.B. mustermann statt Mustermann).

Autowerkstätten
Bankkonten
Baumärkte
Bier
Designer-Sonnerbrillen
Discounter
Drogerien
Expresszustelldienste
Fast Food Restaurants
Fernseher
Freizeitbekleidung
Handys
Investmentfonds
Kaufhäuser
Kfz-Versicherungen
Kopfschmerzmittel
Krankenversicherungen
Laptops
Linienflüge für Privatreisen
Mittelklassewagen
Mobilfunkbetreiber
Papiertaschentücher
PCs/Computer
Spielesoftware
Sportschuhe
Strom
Versandhändler
Waschmaschinen
Waschmittel
Zigaretten

English:
Please provide three known brands/providers for each of the categories listed below. Write all names exclusively in lowercase (e.g., mustermann instead of Mustermann).

Car repair shops
Bank accounts
Hardware stores
Beer
Designer sunglasses
Discounters
Drugstores
Express delivery services
Fast-food restaurants
Television sets
Leisurewear
Mobile phones
Investment funds
Department stores
Car insurance
Headache tablets
Health insurance
Laptops
Scheduled flights
Medium-sized cars

	Mobile network operators Paper tissues PCs/Computers Gaming software Sports shoes Electricity providers Mail-order companies Washing machines Detergents Cigarettes
Response by ChatGPT-3.5	*The answer provided by ChatGPT-3.5 is not disclosed for confidentiality reasons to not reveal the brands provided by YouGov. Details are available on request.*

Appendix D: Additional Descriptive Statistics

Tables A7 to A9 present additional descriptive statistics based on the full dataset with 13,991 observations from 5,053 respondents. First, Table A7 and Table A8 display the values and wave-to-wave changes in risk reduction and social demonstrance. Significant changes are assessed based on pairwise t-tests with Bonferroni correction ($p < 0.05$). For risk reduction, 7 out of 120 possible wave-to-wave category-level changes are significant (5.83%). In the case of social demonstrance, the number of significant wave-to-wave category-level changes amounts to 14 out of 120 (11.67%).

Table A9 shows the category rankings based on BRiC in each wave. Rankings of categories display relative changes in BRiC, which go beyond the effect of an overall change in BRiC over the observation period. A striking relative change in the ranking can be observed for medium-sized cars, which ranked seven in 2006 but advanced to rank one in 2016 following the Volkswagen emission scandal in 2015 (BBC 2015).

Table A10 shows the descriptive statistics and the correlations of BRiC, risk reduction, social demonstrance, the dynamic category variables, and the macro variable using the model dataset with 8,977 observations and 3,785 respondents.

Table A7: Means and Changes in Risk Reduction by Category and Wave

Category	2006	2010	2013	2016	2019	Diff_06_10 (in %)	Diff_10_13 (in %)	Diff_13_16 (in %)	Diff_16_19 (in %)	Diff_06_19 (in %)
Bank accounts	3.76	3.93	4.23	4.13	4.14	4.52	7.63	-2.36	0.24	10.11
Beer	4.74	4.89	4.16	4.73	4.45	3.16	-14.93	13.70	-5.92	-6.12
Car insurances	3.75	3.31	3.76	3.95	4.25	-11.73	13.60	5.05	7.59	13.33
Car repair shops	3.28	3.60	3.13	3.61	3.84	9.76	-13.06	15.34	6.37	17.07
Cigarettes	4.13	3.67	3.31	4.54	4.34	-11.14	-9.81	**37.16**	-4.41	5.08
Department stores	3.59	3.43	4.08	4.01	3.76	-4.46	**18.95**	-1.72	-6.23	4.74
Designer sunglasses	4.07	4.49	3.58	4.33	4.33	10.32	-20.27	20.95	0.00	6.39
Detergents	3.59	3.87	3.78	3.63	4.08	7.80	-2.33	-3.97	12.40	13.65
Discounter	3.52	3.64	3.80	3.59	3.52	3.41	4.40	-5.53	-1.95	0.00
Drugstores	3.69	3.15	3.61	3.95	3.76	**-14.63**	14.60	9.42	-4.81	1.90
Electricity providers	2.52	2.68	3.60	3.43	3.62	6.35	**34.33**	-4.72	5.54	**43.65**
Express delivery services	3.44	3.85	3.49	4.58	4.84	11.92	-9.35	**31.23**	5.68	**40.70**
Fast-food restaurants	4.25	4.07	3.96	3.97	3.99	-4.24	-2.70	0.25	0.50	-6.12
Gaming software	2.99	3.79	3.56	3.68	3.77	26.76	-6.07	3.37	2.45	26.09
Hardware stores	3.43	3.12	3.73	3.77	3.77	-9.04	19.55	1.07	0.00	9.91
Headache tablets	4.10	3.83	4.21	3.84	3.83	-6.59	9.92	-8.79	-0.26	-6.59
Health insurances	3.12	3.67	3.63	3.95	4.27	17.63	-1.09	8.82	8.10	**36.86**
Investment funds	3.91	4.28	3.70	4.67	4.10	9.46	-13.55	**26.22**	-12.21	4.86
Laptops	4.63	4.62	4.48	4.78	4.80	-0.22	-3.03	6.70	0.42	3.67
Leisurewear	3.69	3.64	3.32	4.17	3.61	-1.36	-8.79	**25.60**	-13.43	-2.17
Mail-order companies	3.87	4.24	3.78	4.32	4.40	9.56	-10.85	14.29	1.85	13.70
Medium-sized cars	4.37	4.22	4.27	4.94	4.78	-3.43	1.18	15.69	-3.24	9.38
Mobile network operators	3.37	3.63	4.12	3.83	4.22	7.72	13.50	-7.04	10.18	**25.22**
Mobile phones	4.71	4.56	4.20	4.70	4.76	-3.18	-7.89	11.90	1.28	1.06
Paper tissues	3.17	3.24	3.58	3.29	3.00	2.21	10.49	-8.10	-8.81	-5.36
Personal computers	3.83	4.31	4.34	4.67	4.08	12.53	0.70	7.60	-12.63	6.53
Scheduled flights	4.02	3.79	4.05	4.38	4.43	-5.72	6.86	8.15	1.14	10.20
Sports shoes	3.81	4.48	4.08	4.70	4.29	17.59	-8.93	15.20	-8.72	12.60
Television sets	4.62	4.53	4.16	4.43	4.76	-1.95	-8.17	6.49	7.45	3.03
Washing machines	4.50	4.29	4.97	4.42	4.54	-4.67	15.85	-11.07	2.71	0.89
Mean	3.82	3.89	3.89	4.17	4.14	2.61	1.02	7.70	-0.29	9.81

Notes: Values in bold indicate significant changes using pairwise t-tests with Bonferroni correction ($p < 0.05$). Mean values are averaged across categories.

Table A8: Means and Changes in Social Demonstrance by Category and Wave

Category	2006	2010	2013	2016	2019	Diff_06_10 (in %)	Diff_10_13 (in %)	Diff_13_16 (in %)	Diff_16_19 (in %)	Diff_06_19 (in %)
Bank accounts	1.94	2.00	2.72	2.77	2.29	3.09	**36.00**	1.84	-17.33	18.04
Beer	2.45	2.21	2.34	2.46	2.54	-9.80	5.88	5.13	3.25	3.67
Car insurances	1.66	1.74	2.45	2.26	2.28	4.82	**40.80**	-7.76	0.88	37.35
Car repair shops	1.54	1.77	1.96	2.46	2.52	14.94	10.73	25.51	2.44	**63.64**
Cigarettes	2.11	2.06	2.01	2.35	2.50	-2.37	-2.43	16.92	6.38	18.48
Department stores	1.67	1.84	2.28	2.51	2.44	10.18	23.91	10.09	-2.79	**46.11**
Designer sunglasses	2.21	2.44	2.56	2.88	3.20	10.41	4.92	12.50	11.11	**44.80**
Detergents	1.45	1.53	2.09	2.20	2.36	5.52	**36.60**	5.26	7.27	**62.76**
Discounter	1.59	1.82	2.34	2.18	2.17	14.47	**28.57**	-6.84	-0.46	**36.48**
Drugstores	1.63	1.60	2.16	2.35	2.45	-1.84	**35.00**	8.80	4.26	**50.31**
Electricity providers	1.34	1.59	2.26	2.21	2.08	18.66	**42.14**	-2.21	-5.88	**55.22**
Express delivery services	1.69	1.54	2.11	2.83	2.68	-8.88	37.01	**34.12**	-5.30	**58.58**
Fast-food restaurants	1.54	1.65	2.13	2.41	2.41	7.14	29.09	13.15	0.00	**56.49**
Gaming software	1.45	1.69	2.37	2.45	2.40	16.55	40.24	3.38	-2.04	**65.52**
Hardware stores	1.57	1.52	2.47	2.27	2.42	-3.18	**62.50**	-8.10	6.61	**54.14**
Headache tablets	1.52	1.63	2.23	2.06	2.20	7.24	36.81	-7.62	6.80	**44.74**
Health insurances	1.40	1.63	2.52	2.45	2.40	16.43	**54.60**	-2.78	-2.04	**71.43**
Investment funds	1.96	1.63	2.48	2.83	2.42	-16.84	**52.15**	14.11	-14.49	23.47
Laptops	1.82	2.02	2.51	2.59	2.77	10.99	24.26	3.19	6.95	**52.20**
Leisurewear	2.00	2.24	2.22	2.52	2.36	12.00	-0.89	13.51	-6.35	18.00
Mail-order companies	1.66	1.82	2.15	2.22	2.63	9.64	18.13	3.26	18.47	**58.43**
Medium-sized cars	2.16	2.31	2.43	2.74	2.68	6.94	5.19	12.76	-2.19	24.07
Mobile network operators	1.68	1.73	2.40	2.14	2.33	2.98	**38.73**	-10.83	8.88	**38.69**
Mobile phones	1.94	1.88	2.44	2.84	2.73	-3.09	29.79	16.39	-3.87	**40.72**
Paper tissues	1.41	1.38	1.99	1.96	1.97	-2.13	**44.20**	-1.51	0.51	**39.72**
Personal computers	1.77	1.95	2.25	2.56	2.04	10.17	15.38	13.78	-20.31	15.25
Scheduled flights	1.70	1.66	2.35	2.51	2.10	-2.35	**41.57**	6.81	-16.33	23.53
Sports shoes	1.78	1.98	2.47	2.72	2.23	11.24	24.75	10.12	-18.01	25.28
Television sets	1.65	1.74	2.25	2.41	2.46	5.45	29.31	7.11	2.07	**49.09**
Washing machines	1.73	1.72	2.48	2.11	2.24	-0.58	**44.19**	-14.92	6.16	29.48
Mean	1.73	1.81	2.31	2.44	2.41	4.93	29.64	5.84	-0.85	40.86

Notes: Values in bold indicate significant changes using pairwise t-tests with Bonferroni correction ($p < 0.05$). Mean values are averaged across categories.

Table A9: Rankings of BRiC Across Categories

Rank	2006		2010		2013		2016		2019	
1	Beer	4.72	Beer	4.26	Washing machines	4.36	Medium-sized cars	4.63	Cigarettes	4.56
2	Cigarettes	4.62	Laptops	4.06	Bank accounts	3.97	Cigarettes	4.47	Mobile phones	4.35
3	Mobile phones	4.62	Cigarettes	4.04	Medium-sized cars	3.79	Laptops	4.38	Medium-sized cars	4.30
4	Designer sunglasses	4.19	Mobile phones	3.87	Headache tablets	3.79	Beer	4.36	Beer	4.26
5	Television sets	4.19	Medium-sized cars	3.74	Laptops	3.75	Personal computers	4.34	Express delivery services	4.26
6	Laptops	4.17	Personal computers	3.73	Personal computers	3.69	Mobile phones	4.31	Laptops	4.20
7	Medium-sized cars	4.11	Investment funds	3.71	Television sets	3.67	Investment funds	4.22	Television sets	4.11
8	Headache tablets	4.08	Designer sunglasses	3.68	Beer	3.65	Sports shoes	4.18	Washing machines	4.04
9	Washing machines	4.06	Washing machines	3.52	Mobile phones	3.62	Washing machines	3.95	Investment funds	3.90
10	Fast-food restaurants	3.89	Sports shoes	3.52	Mobile network operators	3.54	Designer sunglasses	3.92	Designer sunglasses	3.90
11	Scheduled flights	3.66	Fast-food restaurants	3.49	Sports shoes	3.51	Television sets	3.84	Mail-order companies	3.87
12	Investment funds	3.64	Bank accounts	3.48	Fast-food restaurants	3.47	Express delivery services	3.77	Sports shoes	3.84
13	Sports shoes	3.64	Headache tablets	3.42	Detergents	3.46	Scheduled flights	3.75	Detergents	3.82
14	Personal computers	3.52	Television sets	3.38	Health insurances	3.38	Fast-food restaurants	3.61	Scheduled flights	3.81
15	Mail-order companies	3.42	Detergents	3.38	Scheduled flights	3.36	Leisurewear	3.60	Health insurances	3.74

Table A9: Rankings of BRiC Across Categories (continued)

Rank	2006		2010		2013		2016		2019	
16	Bank accounts	3.26	Mail-order companies	3.37	Hardware stores	3.31	Car insurances	3.59	Bank accounts	3.71
17	Leisurewear	3.17	Scheduled flights	3.17	Cigarettes	3.30	Mail-order companies	3.58	Car insurances	3.68
18	Department stores	3.16	Mobile network operators	3.06	Department stores	3.25	Headache tablets	3.53	Mobile network operators	3.60
19	Car repair shops	3.13	Car repair shops	3.01	Car insurances	3.23	Health insurances	3.46	Headache tablets	3.58
20	Detergents	3.12	Express delivery services	3.00	Investment funds	3.22	Bank accounts	3.44	Personal computers	3.56
21	Drugstores	3.07	Leisurewear	2.98	Electricity providers	3.21	Detergents	3.37	Fast-food restaurants	3.53
22	Mobile network operators	3.03	Health insurances	2.96	Mail-order companies	3.16	Drugstores	3.36	Car repair shops	3.37
23	Discounter	2.99	Discounter	2.82	Designer sunglasses	3.13	Department stores	3.32	Department stores	3.26
24	Hardware stores	2.97	Gaming software	2.79	Gaming software	3.12	Gaming software	3.31	Gaming software	3.23
25	Car insurances	2.86	Car insurances	2.71	Paper tissues	3.10	Car repair shops	3.24	Hardware stores	3.19
26	Paper tissues	2.85	Department stores	2.67	Discounter	3.05	Mobile network operators	3.11	Electricity providers	3.17
27	Health insurances	2.70	Paper tissues	2.65	Drugstores	2.94	Discounter	3.07	Leisurewear	3.16
28	Express delivery services	2.63	Drugstores	2.59	Express delivery services	2.93	Hardware stores	2.95	Drugstores	3.07
29	Gaming software	2.33	Hardware stores	2.39	Car repair shops	2.79	Electricity providers	2.89	Discounter	2.93
30	Electricity providers	1.91	Electricity providers	2.29	Leisurewear	2.65	Paper tissues	2.80	Paper tissues	2.51

Table A10: Descriptive Statistics

Variables	**N**	**Mean**	**SD**	**Max**	**Min**				
BRiC	8,977	3.472	1.774	7.000	1.000				
Risk reduction	8,977	4.030	1.811	7.000	1.000				
Social demonstrance	8,977	2.278	1.574	7.000	1.000				
Brand strength average	8,977	11.539	8.123	34.560	-3.903				
Brand strength variation	8,977	9.289	4.707	22.498	1.486				
Power of category leader	8,977	8.262	6.534	25.907	0.066				
Number of brands	8,977	11.792	9.310	50.000	2.000				
Negative publicity	8,977	-4.473	4.115	2.987	-20.551				
Business cycle	8,977	-0.006	0.021	0.018	-0.041				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
BRiC	1.000								
Risk reduction	0.807***	1.000							
Social demonstrance	0.520***	0.435***	1.000						
Brand strength average	0.017	0.041***	0.017	1.000					
Brand strength variation	0.008	0.029**	0.002	0.287***	1.000				
Power of category leader	-0.002	0.020	-0.011	0.185***	0.449***	1.000			
Number of brands	0.076***	0.055***	0.049***	-0.312***	-0.059***	-0.153***	1.000		
Negative publicity	0.030**	0.000	0.025*	-0.848***	-0.389***	-0.254***	0.334***	1.000	
Business cycle	0.103***	0.061***	0.145***	0.017	-0.049***	-0.066***	0.280***	0.098***	1.000

Notes: Due to space limits, consumer-level factors and static category variables are not displayed.
*p < 0.10, **p < 0.05, ***p < 0.01.

Appendix E: Robustness Checks

Several robustness checks were performed to validate the results of the main analyses. First, a model with random intercepts for respondents and categories and random slopes only for respondents was estimated (M2a and M2b; see Table A11). Second, I estimated a category-fixed effects model using category dummies, which required removing all static category variables (M3a and M3b; see Table A12). In doing so, the model highlights the effect of dynamic category factors by controlling for all time-invariant category effects. Similarly, I estimated a time-fixed effects model (M4a and M4b; see Table A13), controlling for all time effects, such as the macroeconomic development or the growth in e-commerce. Thus, in this model, the macro-level variable was excluded. Additionally, the main model (M1a and M1b) was estimated using less informative priors [N(0, 100)] (M5a and M5b; see Table A14) to examine whether coefficient estimates in the main model are affected by the selection of priors. Finally, I estimated a model excluding the categories designer sunglasses, investment funds, health insurance, and gaming software, which can be considered problematic based on the ChatGPT-3.5 coding process (M6a and M6b; see Table A15). Across all models, results demonstrate a high level of robustness. The only exception is the moderating effect of the business cycle, which becomes insignificant in all robustness check models except for the model with less informative priors. Therefore, the positive moderating effect of the business cycle on the relationship between social demonstrance and BRiC should be interpreted with caution. Table A16 summarizes the results of the robustness checks and compares the findings regarding the moderating effects to the main model.

Table A11: Models with Respondent-Specific Random-Slopes Only

DV: BRiC	Expected effects	M2a		M2b	
INTERCEPT		**3.034**	**[2.918, 3.152]**	**3.015**	**[2.894, 3.134]**
RISK		**0.666**	**[0.654, 0.679]**	**0.668**	**[0.648, 0.689]**
RISK x AGE				**0.003**	**[0.002, 0.004]**
RISK x GENDER				-0.005	[-0.030, 0.020]
RISK x EDUCATION				0.002	[-0.025, 0.028]
RISK x BSAVE	(+)			**0.003**	**[0.000, 0.005]**
RISK x BSVA	(+)			0.001	[-0.001, 0.004]
RISK x POWER	(+)			-0.001	[-0.002, 0.001]
RISK x NUMBER	(+)			**0.003**	**[0.002, 0.004]**
RISK x NEGPUB	(+)			**0.008**	**[0.002, 0.013]**
RISK x MACRO	(+/-)			0.254	[-0.336, 0.840]
DEMO		**0.251**	**[0.237, 0.265]**	**0.252**	**[0.230, 0.274]**
DEMO x AGE				**-0.002**	**[-0.003, -0.001]**
DEMO x GENDER				-0.018	[-0.046, 0.009]
DEMO x EDUCATION				0.012	[-0.018, 0.043]
DEMO x BSAVE	(+)			0.002	[-0.001, 0.005]
DEMO x BSVA	(+)			-0.002	[-0.005, 0.001]
DEMO x POWER	(+)			0.001	[-0.001, 0.003]
DEMO x NUMBER	(+/-)			-0.001	[-0.003, 0.000]
DEMO x NEGPUB	(-)			-0.003	[-0.009, 0.003]
DEMO x MACRO	(+)			0.681	[-0.024, 1.392]
AGE		**0.003**	**[0.002, 0.004]**	**0.005**	**[0.003, 0.006]**
GENDER		0.006	[-0.030, 0.042]	0.009	[-0.030, 0.048]
EDUCATION		-0.026	[-0.065, 0.013]	-0.026	[-0.068, 0.016]
BSAVE		0.001	[-0.007, 0.009]	0.002	[-0.006, 0.011]
BSVA		0.004	[-0.003, 0.011]	0.006	[-0.002, 0.013]
POWER		0.000	[-0.004, 0.005]	0.000	[-0.005, 0.004]
NUMBER		0.001	[-0.003, 0.004]	0.002	[-0.002, 0.005]
NEPUB		0.009	[-0.005, 0.023]	0.011	[-0.004, 0.025]
MACRO		-0.585	[-2.497, 1.310]	-0.678	[-2.595, 1.269]
TIME		**0.175**	**[0.131, 0.217]**	**0.179**	**[0.136, 0.222]**
Category controls		Yes		Yes	
$\sigma_{\iota 0}$ (Respondent)		0.385	[0.360, 0.410]	0.383	[0.357, 0.407]
$\sigma_{\iota\beta}$		0.208	[0.195, 0.222]	0.204	[0.191, 0.218]
$\sigma_{\iota\gamma}$		0.208	[0.187, 0.229]	0.201	[0.180, 0.222]
$\sigma_{\upsilon 0}$ (Category)		0.118	[0.082, 0.161]	0.118	[0.082, 0.164]
$\sigma_{\upsilon\beta}$		–		–	
$\sigma_{\upsilon\gamma}$		–		–	
σ_{ε} (Residual)		0.827	[0.814, 0.839]	0.825	[0.813, 0.838]
Bayesian R^2		0.783		0.784	

Notes: Estimates represent posterior means and are unstandardized. The 90% posterior density intervals are indicated in brackets. Bold coefficients indicate that 90% of the posterior density excludes zero (similar to $p < 0.10$ in frequentist statistical modeling). Estimates for static category variables are omitted due to space limits. Number of observations = 8,977, number of individuals = 3,785, number of categories = 28.

Table A12: Models with Category-Fixed Effects

DV: BRiC	Expected effects	M3a		M3b	
INTERCEPT		**3.093**	**[2.921, 3.262]**	**3.074**	**[2.899, 3.249]**
RISK		**0.665**	**[0.653, 0.678]**	**0.668**	**[0.648, 0.688]**
RISK x AGE				**0.003**	**[0.002, 0.004]**
RISK x GENDER				-0.006	[-0.030, 0.018]
RISK x EDUCATION				0.001	[-0.025, 0.029]
RISK x BSAVE	(+)			**0.003**	**[0.000, 0.005]**
RISK x BSVA	(+)			0.001	[-0.001, 0.004]
RISK x POWER	(+)			-0.001	[-0.002, 0.001]
RISK x NUMBER	(+)			**0.003**	**[0.002, 0.004]**
RISK x NEGPUB	(+)			**0.008**	**[0.002, 0.013]**
RISK x MACRO	(+/-)			0.270	[-0.301, 0.862]
DEMO		**0.251**	**[0.237, 0.265]**	**0.251**	**[0.230, 0.274]**
DEMO x AGE				**-0.002**	**[-0.003, -0.001]**
DEMO x GENDER				-0.017	[-0.045, 0.011]
DEMO x EDUCATION				0.012	[-0.018, 0.042]
DEMO x BSAVE	(+)			0.002	[-0.001, 0.005]
DEMO x BSVA	(+)			-0.002	[-0.005, 0.001]
DEMO x POWER	(+)			0.001	[-0.001, 0.003]
DEMO x NUMBER	(+/-)			-0.001	[-0.003, 0.000]
DEMO x NEGPUB	(-)			-0.003	[-0.009, 0.003]
DEMO x MACRO	(+)			0.682	[-0.038, 1.392]
AGE		**0.003**	**[0.002, 0.004]**	**0.005**	**[0.003, 0.006]**
GENDER		0.005	[-0.031, 0.041]	0.007	[-0.032, 0.046]
EDUCATION		-0.025	[-0.064, 0.014]	-0.025	[-0.067, 0.016]
BSAVE		0.002	[-0.008, 0.011]	0.003	[-0.006, 0.013]
BSVA		0.008	[-0.001, 0.017]	**0.010**	**[0.001, 0.020]**
POWER		0.002	[-0.004, 0.008]	0.001	[-0.005, 0.007]
NUMBER		0.002	[-0.003, 0.007]	0.003	[-0.002, 0.008]
NEPUB		0.012	[-0.004, 0.029]	0.014	[-0.002, 0.030]
MACRO		-0.508	[-2.534, 1.492]	-0.649	[-2.706, 1.419]
TIME		**0.166**	**[0.120, 0.212]**	**0.172**	**[0.126, 0.217]**
Category-fixed effects		Yes		Yes	
$\sigma_{\iota 0}$ (Respondent)		0.384	[0.359, 0.409]	0.382	[0.356, 0.407]
$\sigma_{\iota\beta}$		0.208	[0.194, 0.222]	0.204	[0.191, 0.218]
$\sigma_{\iota\gamma}$		0.208	[0.187, 0.229]	0.201	[0.179, 0.222]
$\sigma_{\upsilon 0}$ (Category)		–		–	
$\sigma_{\upsilon\beta}$		–		–	
$\sigma_{\upsilon\gamma}$		–		–	
σ_{ε} (Residual)		0.827	[0.814, 0.839]	0.826	[0.813, 0.839]
Bayesian R^2		0.783		0.784	

Notes: Estimates represent posterior means and are unstandardized. The 90% posterior density intervals are indicated in brackets. Bold coefficients indicate that 90% of the posterior density excludes zero (similar to $p < 0.10$ in frequentist statistical modeling). Estimates for category-fixed effects are omitted due to space limits. Number of observations = 8,977, number of individuals = 3,785, number of categories = 28.

Table A13: Models with Time-Fixed Effects

DV: BRiC	Expected effects	M4a		M4b	
INTERCEPT		**3.148**	**[3.083, 3.212]**	**3.145**	**[3.081, 3.211]**
RISK		**0.672**	**[0.648, 0.697]**	**0.672**	**[0.644, 0.700]**
RISK x AGE				**0.003**	**[0.002, 0.003]**
RISK x GENDER				-0.003	[-0.028, 0.021]
RISK x EDUCATION				0.004	[-0.022, 0.031]
RISK x BSAVE	(+)			**0.004**	**[0.001, 0.008]**
RISK x BSVA	(+)			0.001	[-0.003, 0.005]
RISK x POWER	(+)			0.001	[-0.002, 0.003]
RISK x NUMBER	(+)			**0.002**	**[0.000, 0.004]**
RISK x NEGPUB	(+)			**0.010**	**[0.003, 0.017]**
RISK x MACRO	(+/-)	–		–	
DEMO		**0.248**	**[0.223, 0.273]**	**0.253**	**[0.223, 0.283]**
DEMO x AGE				**-0.002**	**[-0.003, -0.001]**
DEMO x GENDER				-0.020	[-0.047, 0.008]
DEMO x EDUCATION				0.006	[-0.024, 0.037]
DEMO x BSAVE	(+)			0.000	[-0.005, 0.004]
DEMO x BSVA	(+)			-0.002	[-0.006, 0.002]
DEMO x POWER	(+)			0.000	[-0.003, 0.002]
DEMO x NUMBER	(+/-)			0.000	[-0.002, 0.002]
DEMO x NEGPUB	(-)			-0.006	[-0.014, 0.001]
DEMO x MACRO	(+)	–		–	
AGE		**0.003**	**[0.002, 0.004]**	**0.005**	**[0.003, 0.006]**
GENDER		0.004	[-0.030, 0.039]	0.005	[-0.033, 0.044]
EDUCATION		-0.021	[-0.059, 0.018]	-0.017	[-0.059, 0.024]
BSAVE		-0.003	[-0.010, 0.005]	0.000	[-0.008, 0.008]
BSVA		-0.002	[-0.008, 0.004]	0.000	[-0.007, 0.007]
POWER		0.002	[-0.002, 0.006]	0.002	[-0.003, 0.007]
NUMBER		-0.001	[-0.004, 0.002]	0.000	[-0.003, 0.004]
NEPUB		0.000	[-0.013, 0.014]	0.006	[-0.008, 0.020]
MACRO		–		–	
Time-fixed effects		Yes		Yes	
Category controls		Yes		Yes	
$\sigma_{\iota 0}$ (Respondent)		0.383	[0.358, 0.407]	0.381	[0.356, 0.406]
$\sigma_{\iota\beta}$		0.206	[0.192, 0.219]	0.203	[0.189, 0.216]
$\sigma_{\iota\gamma}$		0.204	[0.182, 0.224]	0.200	[0.179, 0.221]
$\sigma_{\upsilon 0}$ (Category)		0.133	[0.097, 0.176]	0.128	[0.094, 0.169]
$\sigma_{\upsilon\beta}$		0.066	[0.050, 0.086]	0.063	[0.047, 0.082]
$\sigma_{\upsilon\gamma}$		0.065	[0.048, 0.086]	0.063	[0.045, 0.086]
σ_{ε} (Residual)		0.818	[0.805, 0.831]	0.817	[0.805, 0.830]
Bayesian R^2		0.788		0.788	

Notes: Estimates represent posterior means and are unstandardized. The 90% posterior density intervals are indicated in brackets. Bold coefficients indicate that 90% of the posterior density excludes zero (similar to $p < 0.10$ in frequentist statistical modeling). Estimates for static category variables and time-fixed effects are omitted due to space limits. Number of observations = 8,977, number of individuals = 3,785, number of categories = 28.

Table A14: Models with Uninformative Priors [N(0, 100)]

DV: BRiC	Expected effects	M5a		M5b	
INTERCEPT		**3.025**	**[2.905, 3.143]**	**3.020**	**[2.904, 3.138]**
RISK		**0.672**	**[0.648, 0.697]**	**0.671**	**[0.643, 0.700]**
RISK x AGE				**0.003**	**[0.002, 0.004]**
RISK x GENDER				-0.004	[-0.028, 0.020]
RISK x EDUCATION				0.003	[-0.024, 0.030]
RISK x BSAVE	(+)			**0.005**	**[0.001, 0.009]**
RISK x BSVA	(+)			0.002	[-0.002, 0.006]
RISK x POWER	(+)			0.001	[-0.002, 0.003]
RISK x NUMBER	(+)			**0.002**	**[0.000, 0.004]**
RISK x NEGPUB	(+)			**0.011**	**[0.004, 0.018]**
RISK x MACRO	(+/-)			-0.035	[-0.651, 0.577]
DEMO		**0.247**	**[0.222, 0.273]**	**0.250**	**[0.220, 0.279]**
DEMO x AGE				**-0.002**	**[-0.003, -0.001]**
DEMO x GENDER				-0.018	[-0.046, 0.010]
DEMO x EDUCATION				0.010	[-0.021, 0.040]
DEMO x BSAVE	(+)			-0.001	[-0.006, 0.003]
DEMO x BSVA	(+)			-0.002	[-0.007, 0.002]
DEMO x POWER	(+)			0.000	[-0.003, 0.003]
DEMO x NUMBER	(+/-)			-0.001	[-0.003, 0.002]
DEMO x NEGPUB	(-)			-0.008	[-0.015, 0.000]
DEMO x MACRO	(+)			**0.847**	**[0.118, 1.573]**
AGE		**0.003**	**[0.002, 0.004]**	**0.005**	**[0.003, 0.006]**
GENDER		0.002	[-0.032, 0.037]	0.004	[-0.034, 0.042]
EDUCATION		-0.028	[-0.066, 0.011]	-0.027	[-0.068, 0.015]
BSAVE		0.002	[-0.006, 0.009]	0.004	[-0.003, 0.012]
BSVA		0.001	[-0.005, 0.008]	0.004	[-0.003, 0.011]
POWER		0.001	[-0.003, 0.005]	0.001	[-0.004, 0.005]
NUMBER		0.000	[-0.003, 0.003]	0.001	[-0.002, 0.005]
NEPUB		0.008	[-0.006, 0.021]	0.013	[-0.001, 0.027]
MACRO		-0.281	[-2.103, 1.591]	-0.441	[-2.345, 1.498]
TIME		**0.176**	**[0.134, 0.218]**	**0.176**	**[0.134, 0.217]**
Category controls		yes		yes	
$\sigma_{\iota 0}$ (Respondent)		0.386	[0.361, 0.411]	0.384	[0.359, 0.409]
$\sigma_{\iota\beta}$		0.205	[0.192, 0.219]	0.202	[0.189, 0.216]
$\sigma_{\iota\gamma}$		0.205	[0.184, 0.226]	0.200	[0.179, 0.222]
$\sigma_{\upsilon 0}$ (Category)		0.128	[0.095, 0.170]	0.125	[0.093, 0.165]
$\sigma_{\upsilon\beta}$		0.065	[0.049, 0.084]	0.061	[0.045, 0.080]
$\sigma_{\upsilon\gamma}$		0.064	[0.047, 0.085]	0.062	[0.044, 0.084]
σ_{ε} (Residual)		0.819	[0.806, 0.832]	0.819	[0.806, 0.832]
Bayesian R^2		0.787		0.787	

Notes: Estimates represent posterior means and are unstandardized. The 90% posterior density intervals are indicated in brackets. Bold coefficients indicate that 90% of the posterior density excludes zero (similar to $p < 0.10$ in frequentist statistical modeling). Estimates for static category variables are omitted due to space limits. Number of observations = 8,977, number of individuals = 3,785, number of categories = 28.

Table A15: Models Excluding Problematic Categories

DV: BRiC	Expected effects	M6a		M6b	
INTERCEPT		**3.077**	**[2.953, 3.199]**	**3.072**	**[2.948, 3.195]**
RISK		**0.678**	**[0.653, 0.704]**	**0.677**	**[0.648, 0.706]**
RISK x AGE				**0.003**	**[0.002, 0.003]**
RISK x GENDER				-0.008	[-0.034, 0.017]
RISK x EDUCATION				0.008	[-0.020, 0.036]
RISK x BSAVE	(+)			**0.005**	**[0.001, 0.009]**
RISK x BSVA	(+)			0.001	[-0.003, 0.005]
RISK x POWER	(+)			0.001	[-0.002, 0.003]
RISK x NUMBER	(+)			**0.002**	**[0.000, 0.004]**
RISK x NEGPUB	(+)			**0.011**	**[0.004, 0.018]**
RISK x MACRO	(+/-)			0.087	[-0.550, 0.713]
DEMO		**0.242**	**[0.218, 0.265]**	**0.245**	**[0.215, 0.275]**
DEMO x AGE				**-0.002**	**[-0.003, -0.001]**
DEMO x GENDER				-0.024	[-0.052, 0.006]
DEMO x EDUCATION				0.017	[-0.014, 0.049]
DEMO x BSAVE	(+)			-0.002	[-0.006, 0.002]
DEMO x BSVA	(+)			-0.002	[-0.006, 0.003]
DEMO x POWER	(+)			0.000	[-0.003, 0.003]
DEMO x NUMBER	(+/-)			0.000	[-0.002, 0.002]
DEMO x NEGPUB	(-)			**-0.009**	**[-0.016, -0.001]**
DEMO x MACRO	(+)			0.688	[-0.066, 1.443]
AGE		**0.003**	**[0.001, 0.004]**	**0.004**	**[0.003, 0.006]**
GENDER		0.002	[-0.035, 0.040]	0.001	[-0.040, 0.041]
EDUCATION		-0.025	[-0.068, 0.016]	-0.021	[-0.066, 0.024]
BSAVE		-0.001	[-0.008, 0.007]	0.003	[-0.006, 0.011]
BSVA		0.001	[-0.005, 0.008]	0.004	[-0.004, 0.011]
POWER		0.000	[-0.005, 0.004]	-0.001	[-0.006, 0.004]
NUMBER		0.000	[-0.003, 0.004]	0.001	[-0.002, 0.005]
NEPUB		0.004	[-0.010, 0.018]	0.010	[-0.005, 0.024]
MACRO		0.993	[-0.947, 2.900]	0.914	[-1.040, 2.892]
TIME		**0.157**	**[0.112, 0.201]**	**0.155**	**[0.110, 0.200]**
Category controls		Yes		Yes	
$\sigma_{\iota 0}$ (Respondent)		0.404	[0.378, 0.430]	0.403	[0.377, 0.429]
$\sigma_{\iota\beta}$		0.204	[0.190, 0.219]	0.201	[0.187, 0.215]
$\sigma_{\iota\gamma}$		0.210	[0.187, 0.233]	0.203	[0.179, 0.225]
$\sigma_{\upsilon 0}$ (Category)		0.136	[0.100, 0.184]	0.133	[0.096, 0.179]
$\sigma_{\upsilon\beta}$		0.064	[0.047, 0.084]	0.059	[0.043, 0.079]
$\sigma_{\upsilon\gamma}$		0.053	[0.036, 0.073]	0.055	[0.037, 0.077]
σ_{ε} (Residual)		0.805	[0.791, 0.819]	0.806	[0.792, 0.820]
Bayesian R^2		0.793		0.793	

Notes: Estimates represent posterior means and are unstandardized. The 90% posterior density intervals are indicated in brackets. Bold coefficients indicate that 90% of the posterior density excludes zero (similar to $p < 0.10$ in frequentist statistical modeling). Estimates for static category variables are omitted due to space limits. Number of observations = 7,895, number of individuals = 3,688, number of categories = 24.

Table A16: Overview of the Robustness Check Results

Moderating Effect	Main model	Random-slope respondents	Category-fixed effects	Time-fixed effects	Uninformative priors	Restricted sample
Risk reduction						
Brand strength average	✓	✓	✓	✓	✓	✓
Brand strength variance	✗	✗	✗	✗	✗	✗
Power of category leader	✗	✗	✗	✗	✗	✗
Number of brands	✓	✓	✓	✓	✓	✓
Negative publicity	✓	✓	✓	✓	✓	✓
Business cycle	✗	✗	✗	–	✗	✗
Social demonstrance						
Brand strength average	✗	✗	✗	✗	✗	✗
Brand strength variance	✗	✗	✗	✗	✗	✗
Power of category leader	✗	✗	✗	✗	✗	✗
Number of brands	✗	✗	✗	✗	✗	✗
Negative publicity	✗	✗	✗	✗	✗	✓
Business cycle	✓	✗	✗	–	✓	✗

Notes: For clarity, only the findings regarding the moderating effects of dynamic category variables and the business cycle are included. ✓ indicates that 90% of the posterior density excludes zero (similar to $p < 0.10$ in frequentist modeling). ✗ indicates that 90% of the posterior density include zero.

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PAPER 2: WHEN DO BRANDS MATTER MORE? THE MODERATING EFFECT OF BRAND RELEVANCE ON FIRM VALUE

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ABSTRACT

Previous literature demonstrates a positive association between brand equity and firm value, while also emphasizing the high heterogeneity across firms. In answer to calls for investigating the underlying reason for the variation in the brand equity-firm value link, this research proposes brand relevance in category (BRiC) as a possible moderator between brand equity and firm value. The current findings highlight a positive moderation effect of BRiC. In categories where brands play an important role in consumer decision-making, the impact of brand equity on stock returns is more positive. This finding has important implications for research and practice. It can explain heterogeneous effects in the brand equity-firm value link across industries and guide managers in their brand investment decisions.

Keywords: Brand relevance in category, firm value, brand value chain, marketing-finance interface

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1 Introduction

For many firms, brands belong to their most valuable assets. According to Interbrand, the 100 most valuable brands accumulated a cumulative brand value of $3.4 trillion in 2024, compared to $988 billion in 2000. Although this may indicate significant growth in the financial relevance of brands for firms, a cumulative brand value potential loss of $3.5 trillion over the past 25 years is reported due to firms focusing on short-term gains (Interbrand 2024). This short-term perspective is a well-known problem in the marketing-finance interface, resulting from the challenges of marketing accountability (Edeling, Srinivasan, and Hanssens 2021; Mizik 2014). Building and maintaining brand equity, defined as the added value of branded products compared to non-branded products (Farquhar 1989; Keller 1993), requires high initial and continuous investments. At the same time, quantifying its total financial impact is not trivial, which drives managers to prefer marketing activities that lead to immediate financial gains over building long-term brand assets (Mizik 2014). While in the short run, the negative effects of brand-building on the firm's financials might dominate, in the long run, brand equity can benefit firms by augmenting the level of cash flows or reducing the uncertainty of cash flows. Firms with strong and differentiated brands can, among other things, enhance consumer responses to marketing activities or attain price and volume premiums (Srivastava, Shervani, and Fahey 1998). Thus, providing evidence for the long-term financial benefits of brand equity is crucial. In this context, firm value has emerged as an important future-oriented and cash-based metric that is independent of accounting choices (Edeling and Fischer 2016; Rappaport 1998; Rust et al. 2004).

Existing literature has highlighted a positive relationship between brand equity and firm value. For example, research shows that the stocks of Interbrand's most valuable brands outperform the market (Fehle et al. 2008; Madden, Fehle, and Fournier 2006) and that the stock market positively reacts to improvements in brand equity (Bharadwaj, Tuli, and Bonfrer 2011;

Mizik and Jacobson 2008). However, not all firms benefit from brand equity in equal forms (Edeling and Fischer 2016; Fischer and Wies 2024). An important contingency factor is the industry in which the firm operates. The industry context can determine the nature (i.e., short-term versus long-term) and magnitude of brand equity's impact on firm value (Mizik 2014; Vomberg, Homburg, and Bornemann 2015). The service sector, for example, is characterized by high intangibility and variability, making it difficult to assess service performance and quality before consumption. Hence, the purchase of services involves greater uncertainty and risks for consumers. Strong brands can help reduce this risk by signaling consistent service quality, whereby the importance of brands for consumers and, consequently, the brands' economic relevance for firms in the service sector increases (Fischer, Völckner, and Sattler 2010; Vomberg, Homburg, and Bornemann 2015).

Fischer, Völckner, and Sattler (2010) define the importance of brands for consumer decision-making across categories as brand relevance in category (BRiC). BRiC is driven by two main brand functions: the ability of the brand to reduce consumer purchasing risk (i.e., the risk reduction function) and the extent to which brands can foster signaling a self-concept or image (i.e., the social demonstrance function). Various product-market characteristics promote differences in BRiC across categories. Brands can reduce consumer purchasing risks more effectively in categories with many brands or where the quality assessment before purchase is difficult (e.g., services). For example, when purchasing a flight ticket, consumers cannot easily assess the quality of the airline and thus may refer to familiar brands to reduce their perceived risk (Erdem and Swait 1998; Fischer, Völckner, and Sattler 2010). By contrast, purchasing daily necessities like paper tissues involves low risks. In this context, consumer decision-making may be primarily driven by factors like price rather than the brand. Hence, BRiC is higher for scheduled flights than for paper tissues. When brands are more relevant to consumers in their decision-making, their willingness to pay premium prices for strong brands and their brand loyalty is higher. Consequently, firms may better capitalize on their brand-building investments in high-BRiC categories than in low-BRiC categories (Fischer, Völckner, and Sattler 2010).

In accordance, existing research emphasizes that marketing activities translate into greater brand equity in high-BRiC categories than in low-BRiC categories (Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020) and that the impact of brand love on profitability is higher for firms in high-BRiC categories (Nguyen and Feng 2021). However, to the best of my knowledge, no research so far has investigated the moderating effect of BRiC on firm value. I aim to close this gap, providing a complete picture of the role of BRiC in creating long-term value for firms. This can lend theory and practice a possible explanation for the observed heterogeneity in the brand equity-firm value link and guide brand investment decisions.

Additionally, this research is the first to investigate the effect of BRiC by incorporating data from several years. So far, research has considered BRiC a cross-sectional and time-invariant construct (Nguyen and Feng 2021). However, recent research shows that BRiC can change significantly over time in light of category-specific or macroeconomic events (Karagür 2025). Therefore, including the respective BRiC values for each year in longitudinal analyses becomes necessary to uncover the true effect of BRiC.

The remainder of this research is structured as follows. First, I provide an overview of the existing literature regarding the impact of brand equity on firm value and the moderating effect of BRiC in the value-creation process of brands for firms. Second, I derive a hypothesis on the moderating effect of BRiC in the brand equity-firm value link. Then, I describe the empirical setting and present the results of the empirical analyses. Finally, this research concludes by discussing the findings and their implications for practice.

2 Theory and Hypothesis Development

2.1 The Impact of Brand Equity on Firm Value

Although brand equity is conceptualized in various ways in existing marketing literature, the consensus is to define brand equity as the value added of branded products compared to non-branded products (Farquhar 1989; Keller 1993). This added value can manifest on three levels: customer mindset, product-market outcomes, and stock market outcomes.

The brand value chain by Keller and Lehmann (2003) combines the three levels by outlining how brands create financial value for firms. It starts with the firm's marketing activities (e.g., advertising) that influence what customers know, think, and feel about the brand, the so-called customer mindset. This is equivalent to what Keller (1993, p.8) describes as customer-based brand equity (CBBE) or "the differential effect of brand knowledge on consumer response to the marketing of the brand". Brand knowledge comprises consumers' awareness, attitudes, and associations toward the brand. Customer mindset, in turn, influences the brand's performance in the marketplace as reflected in price premium, volume premium, revenue premium, or market share (Ailawadi, Lehman, and Neslin 2003; Keller and Lehmann 2003). These product-market outcomes represent sales-based brand equity (SBBE; Datta, Ailawadi, and van Heerde 2017) and provide a dollar value for the brand (Ailawadi, Lehman, and Neslin 2003). Finally, investors, among other factors, consider the brand's performance in the marketplace to derive a value of the brand in the financial market (Keller and Lehmann 2003). Compared to SBBE, this financial-based brand equity (FBBE) measure is more future-oriented as it also incorporates assessments of the future performance impact of the brand (Ailawadi, Lehman, and Neslin 2003; Mizik 2014).

Other frameworks, such as those by Hanssens et al. (2014) and Edeling and Fischer (2016), extend the indirect route from marketing investments to brand performance in the marketplace through customer mindset (mindset route) by a direct route from marketing investments to firm performance (transactions route). The transactions route considers that marketing investments can positively impact sales directly (e.g., through advertising or sales promotions) but simultaneously represent costs that harm the firm's financials (Edeling and Fischer 2016). Likewise, building brand equity requires high investments, which might influence the financial benefit firms can derive from it. Firms might either benefit financially from brand-building activities in later periods (Mizik 2014; Nguyen and Feng 2021) or not at all, depending on whether they already operate at their optimum (Edeling and Fischer 2016) or whether brands are relevant to consumer decision-making (Fischer, Völckner, and Sattler 2010).

Previous research has attempted to link the various stages of the brand value chain to assess the total financial impact of brands. It has examined how customer mindset metrics (or CBBE) align with product-market outcomes (e.g., Datta, Ailawadi, and van Heerde 2017) or reflect in financial-market outcomes (e.g., Mizik and Jacobson 2008). Regarding product-market outcomes, previous studies show a positive relationship between customer mindset metrics and brand performance, such as earnings and profitability (Aaker and Jacobson 2001; Fischer and Wies 2024; Nguyen and Feng 2021). In terms of financial-market outcomes, research indicates that CBBE dimensions such as perceived quality, brand relevance, and energy provide incremental information to accounting measures in explaining stock returns (Aaker and Jacobson 1994; Bharadwaj, Tuli, and Bonfrer 2011; Mizik and Jacobson 2008). Higher CBBE is associated with higher stock returns compared to market benchmarks during economic crises (Johansson, Dimofte, and Mazvancheryl 2012; Huang, Yang, and Zhu 2021) and with lower firm idiosyncratic risk, albeit its association with systematic risk is inconclusive (Bharadwaj, Tuli, and Bonfrer 2011; Rego, Billett, and Morgan 2009). Table 1 summarizes relevant literature on the relationship between CBBE and firm value.

Table 1: Relevant Literature on Brand Equity and Firm Value

Literature	Brand equity measure [a]	Source of brand equity measure	Impact on firm value metrics [b]	Heterogeneity	Sample	Aggregation level	Endogeneity correction	Observation period
Aaker and Jacobson (1994)	Brand quality (dimension)	EquiTrend	Stock returns (+)	–	34 firms (different industries)	Yearly	–	1989-1993
Aaker and Jacobson (2001)	Brand attitude (index)	Techtel Corporation	Stock returns (+)	–	9 firms (high-tech industry)	Quarterly	–	1988-1996
Bharadwaj, Tuli, and Bonfrer (2011)	Brand quality (dimension)	EquiTrend	Stock returns (+) Idiosyncratic risk (-) Systematic risk (+)	–	132 firms (different industries)	Yearly	Three-stage least squares systems-of-equations	2000-2005
Ha, Song, and Erickson (2021)	Brand equity (index and dimensions)	BAV [c]	Systematic risk (-)	Industries	156 firms (different industries)	Yearly	Instrumental variables (IV)	2000-2006
Mizik (2014)	Brand equity (index)	BAV [c]	Stock returns (+)	Industries	444 firms (different industries)	Yearly	Instrumental variables (IV)	2000-2010
Mizik and Jacobson (2008)	Brand equity (dimensions)	BAV [c]	Stock returns (+/n.s. [d])	–	275 companies (different industries)	Waves	–	1993-2004
Rego, Billett, and Morgan (2009)	Brand equity (index)	EquiTrend	Total risk (-) Idiosyncratic risk (-) Systematic risk (-)	–	252 firms (different industries)	Yearly	–	2000-2006
Vomberg, Homburg, and Bornemann (2015)	Brand attitude (index)	EquiTrend	Tobin's q (+)	Industries	174 companies (different industries)	Yearly	–	2002-2009
This research	***Brand equity (index)***	***YouGov***	***Stock returns (n.s.)***	***BRiC***	***49 firms from 22 different categories***	***Monthly***	***Gaussian copula***	***2011-2017***

Notes: [a,b] As the focus of the current research lies on the impact of CBBE on firm value (in specific shareholder value), brand equity comprises CBBE and research building on SBBE or FBBE is excluded. Similarly, findings on accounting-based performance metrics (e.g., return-on-equity) are omitted. [c] BAV = Brand Asset Valuator (Young & Rubicam). [d] n.s. = non-significant.

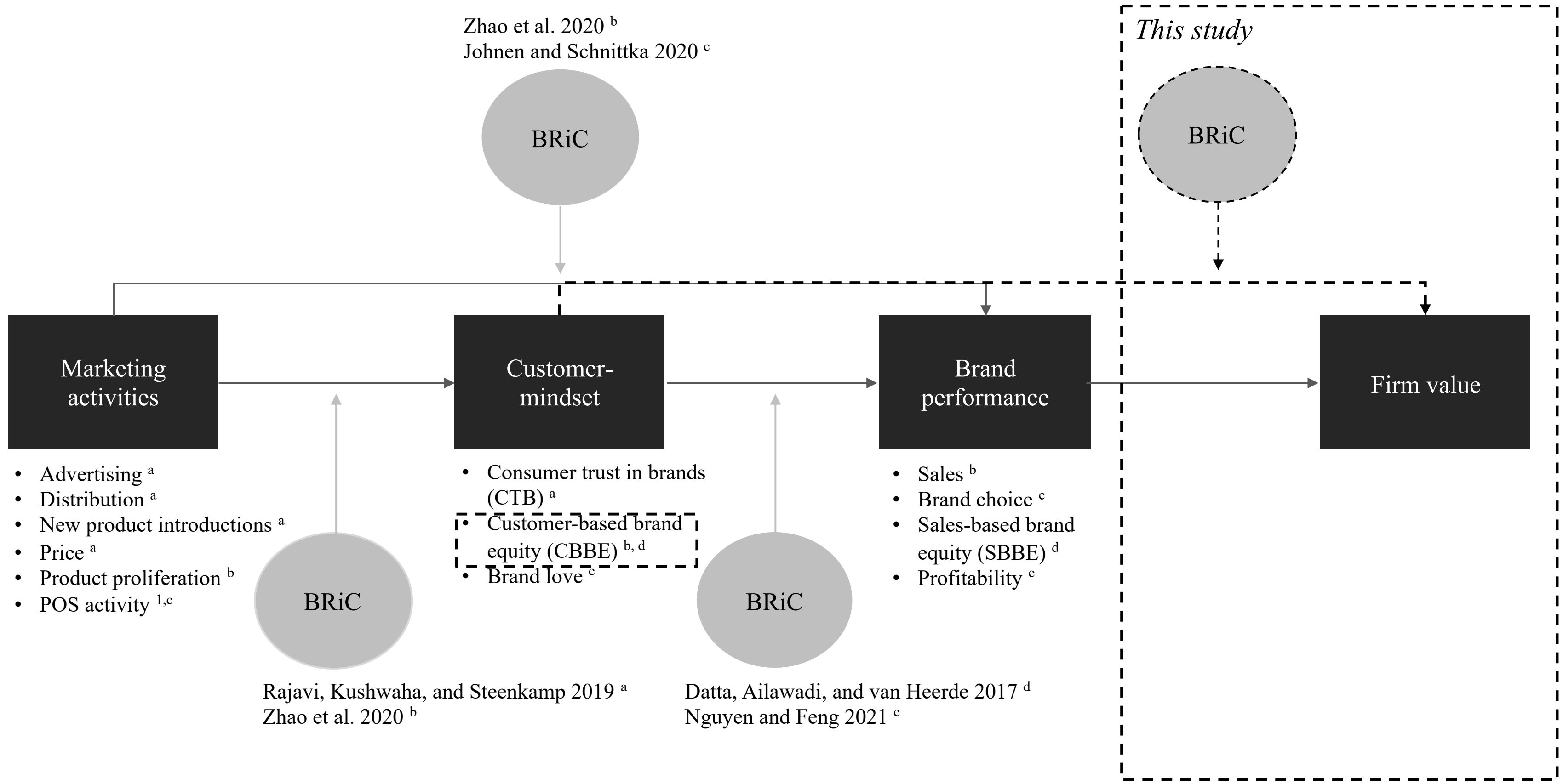
As a generalizable average effect size across studies, the meta-analysis by Edeling and Fischer (2016) shows that a 1% increase in brand-related assets leads to a 0.33% increase in firm value. However, the effect of brand-related assets on firm value varies greatly, with elasticities ranging from -0.43 to 4.72 (Edeling and Fischer 2016), indicating a high heterogeneity in the brand equity-firm value link. In line with this finding, previous research demonstrates that the impact of brand equity on the firm's financial performance differs across firms (Fischer and Wies 2024) and industries (Edeling and Fischer 2016; Ha, Song, and Erickson 2021; Mizik 2014; Vomberg, Homburg, and Bornemann 2015). For example, Ha, Song, and Erickson (2021) highlight that different dimensions of CBBE are relevant for mitigating firm risk across industries. Similarly, Mizik (2014) emphasizes differences across industries in the current- versus future-term financial impact of CBBE. While in the high-tech sector, the effect of brand equity tends to be longer-term (i.e., taking longer to materialize), the opposite can be observed in the restaurant sector, where the effect of brand equity is more immediate. Compared to consumer durables, the impact of brand equity on firm value is higher for service firms, where brands can act as a means for risk reduction (Vomberg, Homburg, and Bornemann 2015). These findings suggest BRiC as a possible moderator between brand equity and firm value.

2.2 The Role of BRiC in the Brand Value Chain

BRiC defines the varying importance of brands for consumer decision-making across categories (Fischer, Völckner, and Sattler 2010). Past research has already demonstrated the moderating role of BRiC along the brand value chain from marketing activities to customer mindset and brand performance (see Figure 1; Datta, Ailawadi, and van Heerde 2017; Johnen and Schnittka 2020; Keller and Lehmann 2003; Nguyen and Feng 2021; Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020). Marketing activities such as advertising, price, distribution, new product introductions, and product proliferation translate into higher consumer trust in brands (CTB) and CBBE in categories where BRiC is high compared to categories where BRiC is low (Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020). In high-BRiC categories, brands are more relevant to consumers' decision-making, so consumers' attention to brand-related marketing and signals is greater (Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020). Conversely, product proliferation has a weaker impact on sales in high-BRiC categories than in low-BRiC categories due to higher brand loyalty and resulting cannibalization effects between existing and new products of the same brand (Zhao et al. 2020). Other moderating effects of BRiC can be found in the relationship between promotional activities at the point of sales and brand choice (Johnen and Schnittka 2020) or the association between CBBE and SBBE (Datta, Ailawadi, and van Heerde 2017). Finally, the effect of brand love on the firm's operating performance is positively moderated by BRiC, which shows that firms can profit more from strong brands financially in high-BRiC categories (Nguyen and Feng 2021).

This research adds to the existing literature in two ways. First, it complements the moderating role of BRiC along the brand value chain by investigating its moderating effect on firm value, specifically stock returns. Considering the shareholder perspective is important to account for the long-term and future-oriented impact of brand equity and paint a holistic picture of the brand's value creation process for firms (Edeling, Srinivasan, and Hanssens 2021; Rust et al. 2004). Although past research indicates that the effect of brand equity on firm value varies across industries (e.g., Mizik 2014; Vomberg, Homburg, and Bornemann 2015), to the best of my knowledge, no research so far has analyzed whether an underlying reason for these heterogenous effects lies in the differing relevance of brands for consumers in their decision-making. This research aims to fill this gap (see Figure 1).

Figure 1: Contribution of Current Research to Existing Literature on BRiC



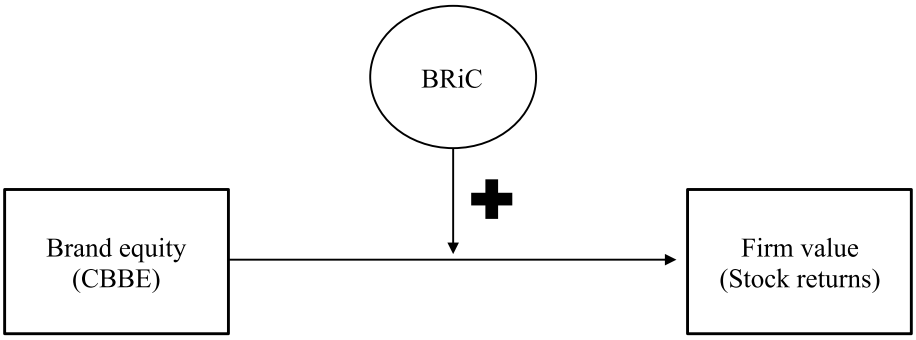
Notes: The figure is adapted from Keller and Lehmann (2003) and Rajavi, Kushwaha, and Steenkamp (2019). The superscripts a, b, c, d, and e indicate which variables are analyzed in the respective research articles. The dotted lines indicate the research gap that the current research is addressing. [1]POS = point of sales.

Second, this research is the first to incorporate several years of BRiC data to account for changes in BRiC over time (Karagür 2025). So far, research investigating the moderating role of BRiC in longitudinal settings has only measured the construct once during the study and considered it a time-invariant cross-sectional variable (Nguyen and Feng 2021). Although BRiC reflects consumers' predisposition toward brands and thus is relatively stable over time, category-specific events (e.g., negative publicity in a category) or macroeconomic conditions can cause notable changes in BRiC (Fischer, Völckner, and Sattler 2010; Karagür 2025). These changes must be accounted for to uncover the true moderating effect of BRiC in longitudinal analyses. Thus, including data on BRiC from several years becomes inevitable.

2.3 The Moderating Effect of BRiC on Firm Value

Following previous research that proposes BRiC as a moderating factor in the relationship between marketing activities, customer mindset, and brand performance (e.g., Rajavi, Kushwaha, and Steenkamp 2019), I establish BRiC as a moderator between customer mindset and firm value. To explain the differing roles of brands for investors across categories, I draw on the Accessibility-Diagnosticity framework by Feldman and Lynch (1988). According to the Accessibility-Diagnosticity framework, the likelihood that certain information is applied for judgment and decision-making depends on (1) the accessibility of that information in the memory and (2) the diagnosticity, i.e., the perceived relevance of the information. In highly visible and expensive categories such as cars, the brand name itself can reduce the perceived purchasing risk of consumers and serve as a status symbol. Thus, BRiC is high in those categories, and consumers pay more attention to brands and prefer brands with higher brand equity. Consequently, strong brands in high-BRiC categories may attain higher price premiums and greater consumer loyalty (Fischer, Völckner, and Sattler 2010). Ultimately, this can lead to better financial outcomes for the firm, as firms can better capitalize on their brand equity financially (Nguyen and Feng 2021). Investors might anticipate this stronger link between brand equity and brand performance in high-BRiC categories and, therefore, consider brand equity and changes in brand equity as more diagnostic for a firm's financial health and their own investment decisions. In addition, brands in high-BRiC categories are generally more accessible to the public as they are more relevant. Considering all these factors, I predict that BRiC will positively moderate the association between brand equity and firm value. Figure 2 depicts the conceptual framework.

Figure 2: Conceptual Framework



3 Methodology

3.1 Data

To analyze the moderating impact of BRiC on the brand equity-firm value link, I combined data from five sources with different time intervals and aggregation levels (see Table 2).

Table 2: Information on Data Specifics

Data source	Data	Frequency of data collection	Observation period	Aggregation level
Yahoo Finance	Data on stock prices	Monthly	2008-2019	Firm
YouGov	Data on brand equity	Daily	2009-2019	Brand
External market research provider	Data on BRiC	Waves	2006, 2010, 2013, 2016, 2019	Category
Kenneth French Data Library	Data on common risk factors	Monthly	2008-2019	–
COMPUSTAT	Data on firm fundamentals	Yearly	2008-2019	Firm

First, an external market research provider collected individual-level survey data from German respondents on BRiC for 30 categories over five waves in 2006, 2010, 2013, 2016, and 2019. I aggregate the individual-level data to obtain yearly BRiC values for the 30 categories. To match the data collection of BRiC from Germany, I also use brand data obtained from German consumers. Brand equity[11] data comes from YouGov, a market research company that monitors brands daily using large online consumer panels. However, using daily brand equity data from YouGov can be problematic due to missing values and small sample sizes per day (Luo, Raithel, and Wiles 2013). Aggregating it to lower frequencies (weekly, monthly, or quarterly) can mitigate these shortcomings and reduce noise. Based on the availability of the other datasets, specifically the common risk factors from Fama and French (1993) and Carhart's (1997) four-factor model, I aggregate brand equity at the monthly level to match it with monthly stock returns and common risk factors. Stock prices are obtained from Yahoo Finance for a global set of firms. The common risk factors of Fama and French (1993) and Carhart's (1997) four-factor model come from the Kenneth French Data Library. Firm fundamentals are obtained from COMPUSTAT and come in quarterly or yearly frequencies. As some companies in the COMPUSTAT global dataset only report financial data bi-quarterly, I use annual firm fundamentals from COMPUSTAT to avoid handling missing data.

[11] Note that the brand equity measure used in this research is CBBE but will be referred to as brand equity hereinafter.

3.2 Sample of Firms and Final Dataset

The sample of firms is global and restricted by the fact that they must be included in the YouGov dataset, be publicly listed, follow a corporate branding strategy for better attribution with stock returns (e.g., Johansson, Dimofte, and Mazvancheryl 2012), and be categorized into one of the 30 BRiC categories. The YouGov data set, which has been used extensively in previous marketing research in different contexts, such as media coverage of corporate social irresponsibility (Stäbler and Fischer 2020), investor attention (Borah et al. 2022), or the effect of firm layoff announcements (Stäbler et al. 2023), constitutes the starting point. At the beginning of 2020, YouGov tracked 1,326 brands in Germany. Three independent coders categorized all 1,326 brands monitored by YouGov in Germany into the 30 BRiC categories. The intercoder agreement was high (> 98%), and any disagreement was resolved through discussions. 393 unique brands could be matched to one of the 28 out of 30 BRiC categories (see also Karagür 2025). Among these 393 brands, only 53 were corporate brands and belonged to publicly listed firms included in COMPUSTAT from 2008 to 2019.

The final dataset is merged as follows. For every firm *i* in month *t*, stock returns and the four risk factors are from the same month *t*, brand equity is from month *t–1*, and BRiC and firm financials come from the previous year. For example, for stock returns from February 2011, brand equity data comes from January 2011, and BRiC and firm financials are from the year 2010. As BRiC data is only available for specific years, the final data set covers only 2011, 2014, and 2017. This leads to 1,537 firm-month observations by 49 unique firms included in at least one of the relevant years.

3.3 Measures

3.3.1 Firm value and risk factors

In this research, firm value is operationalized as excess returns ($EXRET_{it}$) defined as the adjusted stock returns of firm i in month t minus the risk-free rate of return in month t[12]. Following Fama and French (1993) and Carhart (1997), I include the average market return ($RMRF_t$), the size factor (SMB_t), the value factor (HML_t), and the momentum factor (UMD_t) as additional variables in the model to account for common risk factors.

3.3.2 Brand equity

Brand equity is obtained from YouGov. It is based on YouGov's BrandIndex measure, which consists of the six dimensions general impression, quality, value, satisfaction, reputation, and recommendation, and ranges from -100 to +100. Although YouGov tracks consumer responses in over 50 countries, I refer to the German data to match the BRiC data obtained from German consumers. In Germany, YouGov monitors 1,326 brands, surveying over 2,500 respondents per day. For each of the 49 firms, I download the daily BrandIndex score of the respective brand and aggregate it to a monthly frequency. Further details on the brand equity metric are provided in Appendix A.

3.3.3 BRiC data

Data on BRiC comes from an external market research firm, which collected individual-level data on 30 categories covering durables, FMCG, services, and retail in the years 2006, 2010, 2013, 2016, and 2019. The final sample includes 13,991 observations from 5,053 unique respondents. BRiC for durables and FMCG was measured using the following four items *1)*

[12] To match the common risk factors from the Kenneth French Data Library in U.S. dollars, I convert the monthly adjusted stock prices of all firms in U.S. dollars before calculating the monthly stock returns and subtracting the risk-free rate of return. The exchange rates are downloaded from Yahoo Finance. For September 2017, the exchange rate South Korean won-U.S. dollars display an uncommon value, which is imputed using the average of the preceding and proceeding month. Note that this anomaly only affects one observation in the final dataset. Thus, its impact on the model results should be limited.

When I purchase a product in the given category, the brand plays –compared to other things– an important role, 2*) When purchasing, I focus mainly on the brand, 3) To me, it is important to purchase a brand name product, and 4) The brand plays a significant role as to how satisfied I am with the product.*[13] The items were slightly adapted for service and retail categories. Factor analyses using the pooled dataset were conducted to validate that the four items constitute the BRiC scale. The results confirmed the one-factor solution (see Appendix B). Cronbach's alpha is 0.94, indicating good internal validity. Thus, I take the mean of the four items to construct the BRiC scale. Table 3 shows the BRiC scores for each category and year.

Table 3: BRiC Values Across Categories and Years

Category	2006	2010	2013	2016	2019
Bank accounts	3.26	3.48	3.97	3.44	3.71
Beer	4.72	4.26	3.65	4.36	4.26
Car insurances	2.86	2.71	3.23	3.59	3.68
Car repair shops	3.13	3.01	2.79	3.24	3.37
Cigarettes	4.62	4.04	3.30	4.47	4.56
Department stores	3.16	2.67	3.25	3.32	3.26
Designer sunglasses	4.19	3.68	3.13	3.92	3.90
Detergents	3.12	3.38	3.46	3.37	3.82
Discounter	2.99	2.82	3.05	3.07	2.93
Drugstores	3.07	2.59	2.94	3.36	3.07
Electricity providers	1.91	2.29	3.21	2.89	3.17
Express delivery services	2.63	3.00	2.93	3.77	4.26
Fast-food restaurants	3.89	3.49	3.47	3.61	3.53
Gaming software	2.33	2.79	3.12	3.31	3.23
Hardware stores	2.97	2.39	3.31	2.95	3.19
Headache tablets	4.08	3.42	3.79	3.53	3.58
Health insurances	2.70	2.96	3.38	3.46	3.74
Investment funds	3.64	3.71	3.22	4.22	3.90
Laptops	4.17	4.06	3.75	4.38	4.20
Leisurewear	3.17	2.98	2.65	3.60	3.16
Mail-order companies	3.42	3.37	3.16	3.58	3.87
Medium-sized cars	4.11	3.74	3.79	4.63	4.30
Mobile network operators	3.03	3.06	3.54	3.11	3.60
Mobile phones	4.62	3.87	3.62	4.31	4.35
Paper tissues	2.85	2.65	3.10	2.80	2.51
Personal computers	3.52	3.73	3.69	4.34	3.56
Scheduled flights	3.66	3.17	3.36	3.75	3.81
Sports shoes	3.64	3.52	3.51	4.18	3.84
Television sets	4.19	3.38	3.67	3.84	4.11
Washing machines	4.06	3.52	4.36	3.95	4.04
Mean	**3.46**	**3.26**	**3.38**	**3.68**	**3.68**

Notes: Yearly mean values are averaged across categories.

[13] Note that the items have been translated from German.

Across years, categories with the lowest BRiC values include electricity providers, paper tissues, and gaming software, while the categories with the highest mean BRiC constitute the medium-sized cars, mobile phones, and beer categories (see Appendix D). Each firm is assigned the BRiC scores of the respective category to which it was categorized by the coders. If a firm is categorized into multiple categories, the BRiC score is calculated as the average of all categories (see Nguyen and Feng [2021] for a similar approach).

3.3.4 Control variables

In addition to the common risk factors from Fama and French (1993) and Carhart's (1997) four-factor model, I use a set of financial control variables from previous research (Malshe, Colicev, and Mittal 2020). Specifically, I use capital intensity, profit margin, leverage, and R&D intensity as controls. Additionally, I control for the firm's industry (service versus manufacturing based on two-digit NAICS classification) and year-fixed effects. Table 4 provides an overview of all variables and their operationalization.

3.3.5 Unanticipated changes

The efficient market hypothesis posits that the stock market only reacts to new unexpected information, while all other information is already incorporated in the stock price (Mizik and Jacobson 2008). Therefore, I follow previous research (Malshe, Colicev, and Mittal 2020) and operationalize the unexpected changes in the predictor variables brand equity, capital intensity, profit margin, leverage, and R&D intensity as the residual of a first-order autoregressive (AR[1]) model. For each firm *i* and $variable_{it}$, I estimate the following AR(1) model using all available data points:

$$variable_{it} = \phi_0 + \phi_1 variable_{it-1} + \mu_{it}, \quad (1)$$

where *i* denotes the firm and *t* denotes the month. ϕ_1 is the estimate for the autoregressive process and μ_{it} represents the residuals. The residuals in the AR(1) model capture only new unexpected information in time *t* as expected changes are captured by the autoregressive process and all time-invariant fixed effects are included in the intercept ϕ_0 (Greene 2003). Thus, using the residuals μ_{it} as a measure of unexpected changes removes the requirement to include firm-specific fixed effects in any other second-stage estimation (see Malshe, Colicev, and Mittal 2020 for a similar approach).

Table 4: Overview of Variable Operationalization

Variable	Description	Source
Dependent variable		
Excess returns [EXRET]	Stock returns minus the risk-free return.	Yahoo Finance
Independent variable		
Brand equity [BE]	Multidimensional index that reflects the consumers' overall perception of the brand as the average of six dimensions.	YouGov
Moderator variable		
BRiC [BRiC]	Brand relevance in category as the average of four items.	External market research company
Control variables		
Market factor [RMRF]	Risk-free adjusted market return.	Kenneth French Data Library
Small-minus-big factor [SMB]	Differential return between small and large firms.	Kenneth French Data Library
High-minus-low factor [HML]	Differential return between value and growth firms.	Kenneth French Data Library
Momentum factor [UMD]	Differential return between portfolios of firms with rising versus declining stock returns.	Kenneth French Data Library
Capital intensity [CV_1]	The sum of property, plant, and equipment divided by total assets.	COMPUSTAT
Profit margin [CV_2]	Operating income after depreciation divided by total sales.	COMPUSTAT
Leverage [CV_3]	Total liabilities divided by total assets.	COMPUSTAT
R&D intensity [CV_4]	R&D expenditures divided by total sales [a].	COMPUSTAT
Service dummy [SERVICE]	Service dummy indicating whether firm is a service firm based on the two-digit NAICS classification.	COMPUSTAT
Year dummy [Y]	Year dummies for years.	–

Notes: [a] Following past research (Fischer and Wies 2024), missing values for R&D expenditures are imputed with 0 before dividing by total sales.

3.4 Model Specification

Stock return response models are a common method to investigate the incremental effect of brand equity and possible moderators on stock returns (Mizik and Jacobson 2008; Srinivasan and Hanssens 2009). I define the stock return response model as follows:

$$\begin{aligned} EXRET_{it} = {} & \beta_0 + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t \\ & + \beta_5 SERVICE_i + \beta_6 BRIC_{it} + \gamma_1 BE_{it-1} \\ & + \gamma_2 BE_{it-1} \times BRIC_{it} + \gamma_3 Copula_{it-1} + \sum_{k=1}^{K} \delta_k \, CV_{k,it} \\ & + \sum_{y=1}^{Y} \eta_y \, Y_{yt} + \varepsilon_{it}, \end{aligned} \tag{2}$$

where, for each firm i and month t, $EXRET_{it}$ is the excess return of firm i in month t, $RMRF_t$ is the risk-free adjusted market return in month t, SMB_t is the size factor describing the return difference between small and large firms in month t, HML_t is the value factor capturing the return difference between value and growth firms in month t, UMD_t is the momentum factor in month t accounting for the differential return between portfolios of firms with rising versus declining stock returns. BE_{it-1} is the brand equity[14] of firm i in the previous month *t–1*. $BRIC_{it}$ is the average brand relevance in category of firm i in month t. $CV_{k,it}$ describes a set of financial control variables, namely capital intensity, profit margin, leverage, and R&D intensity. Note that $BRIC_{it}$ and $CV_{k,it}$ represent values from the previous year and thus do not change within a year across months but only across firms. $SERVICE_i$ is a dummy variable for service firms and Y_{yt} represents year dummy variables. ε_{it} is the residual with N(0, σ_ε^2). $Copula_{it-1}$ is a Gaussian copula correction for brand equity that accounts for its possible endogeneity. The following section describes the endogeneity problem in detail.

[14] Note that in the following variable names for brand equity, capital intensity, profit margin, leverage, and R&D intensity refer to unanticipated changes in the respective variables if not specified otherwise.

3.5 Addressing Endogeneity

Two major identification problems might be of concern in the current research: simultaneity (reverse causality) and omitted variable bias (Germann, Ebbes, and Grewal 2015). I discuss and address these endogeneity concerns in the following.

3.5.1 Simultaneity and reverse causality

First, one can argue that stock returns influence brand equity, indicating a reverse causality. As firm value is a forward-looking measure, an unexpected rise in stock returns might signal a superior anticipated performance of firms. In response, consumers might adjust their perception of the brand accordingly. Additionally, high changes in stock prices are more likely to be reported in the media, thus influencing consumer brand perceptions. To control for this simultaneity effect, I lag the brand equity variable by one month. Similarly, BRiC and the financial control variables are from the previous year. This ensures that stock market participants have enough time to react to category and performance changes of firms. In addition, Karagür (2025) shows that the average brand equity in a category can impact BRiC. Even though a strategic influence of BRiC requires that several firms in the category act in a coordinated way, lagging BRiC by one year removes this simultaneity concern.

3.5.2 Omitted variables

Another endogeneity concern pertains to an omitted variable bias at the time and firm level. Time-variant unobserved factors such as macroeconomic conditions (e.g., recessions) might influence brand equity, BRiC, and stock market developments, leading to biased and inconsistent estimates (Greene 2003). I control for these time-related effects by including Fama and French’s (1993) and Carhart’s (1997) common risk factors and year dummy variables. The year dummy variables should capture all time-specific effects that do not vary across firms, such as macroeconomic conditions (e.g., recessions).

Similarly, unobserved firm-level characteristics such as manager capabilities might simultaneously impact the firm's brand equity and stock market performance. I control for unobserved cross-sectional factors in two ways. First, I operationalize the time-variant variables as unanticipated changes using the residuals from a first-order autoregressive model (AR[1]). As I estimate the AR(1) model for each firm separately, firm-specific effects are captured in the intercept, leaving only the within-firm variation in the variables (Germann, Ebbes, and Grewal 2015).

Still, endogeneity concerns might arise due to time-variant firm-specific factors. For example, a firm's advertising spending might simultaneously impact brand equity and stock performance (Edeling and Fischer 2016). Since I do not have access to monthly advertising data, capturing advertising effects is challenging. An approximation would be to use yearly advertising data from COMPUSTAT. However, a major concern about advertising data from COMPUSTAT is the handling of missing values. Shi, Grewal, and Sridhar (2021) demonstrate that firms' decisions to disclose or not disclose advertising spending can be strategic. This, again, can lead to endogeneity problems. In addition, other unobserved factors might simultaneously influence brand equity and stock performance, which cannot all be captured in the model. To address the remaining endogeneity concerns due to omitted variables, I apply the Gaussian copula approach proposed by Park and Gupta (2012).

3.5.3 Gaussian copula approach

Frequently applied methods to address endogeneity rely on identifying strong and valid instrumental variables (IVs) that correlate highly with the potential endogenous variable but not with the error term of the main regression model. While the strength of an IV can empirically be tested, its validity can only theoretically be argued. This raises concerns regarding its application, as using weak and invalid IVs can lead to biased estimates (Papies, Ebbes, and van Heerde 2017; Rossi 2014).

In the current case, identifying a suitable IV that is strongly related to brand equity but not to unobserved factors affecting stock returns is difficult. Thus, I adopt the Gaussian copula approach proposed by Park and Gupta (2012), which directly models the joint distribution between the potentially endogenous variable and the error term using a copula function, thereby providing an IV-free method to address endogeneity (Rutz and Watson 2019). Following past research (e.g., Datta, Ailawadi, and van Heerde 2017; Zhao et al. 2020), I estimate the copula term for brand equity using the inverse normal cumulative distribution function Φ^{-1} and the empirical cumulative distribution function *H* as follows:

$$Copula_{it-1} = \Phi^{-1}(H(BE_{it-1})) \tag{3}$$

where BE_{it-1} is the brand equity of firm i in month *t-1*. Similar to the control function approach (Petrin and Train 2010), the estimated copula term $Copula_{it-1}$ is inserted as an additional predictor variable in the main regression model (Equation 2) to address potential endogeneity concerns regarding brand equity and its interaction with BRiC (Papies, Ebbes, and van Heerde 2017).

An important requirement for the application of the Gaussian copula approach is that the potentially endogenous variable is not normally distributed. Otherwise, the estimates can be biased, especially for smaller sample sizes (Becker, Proksch, and Ringle 2022). I, therefore, carefully assess the non-normality of brand equity using the Anderson–Darling and Cramer-van Mieses nonnormality tests (as proposed by Becker, Proksch, and Ringle 2022) and by visual inspection of the variable's density and quantile-quantile (QQ) plots. The results of the Anderson–Darling and Cramer-van Mieses nonnormality tests confirm the nonnormality of brand equity ($p < 0.001$). Visual inspections further support this notion (see Appendix E).

4 Results

4.1 Model-Free Analyses

The final data set consists of 49 unique firms from 22 BRiC categories. 44 out of 49 firms are available in all three years (2011, 2014, and 2017). Table 5 displays the number of firms in each BRiC category and an exemplary firm.

Table 5: Number of Firms in Each Category

BRiC category	Number of firms	Example firm
Bank accounts	3	Deutsche Bank
Beer	1	Carlsberg
Car insurances	1	Allianz
Designer sunglasses	1	Hugo Boss
Electricity providers	2	E.on
Express delivery services	3	Deutsche Post
Fast-food restaurants	2	McDonald's
Gaming software	1	Sony
Hardware stores	1	Hornbach
Health insurances	1	Allianz
Investment funds	2	Deutsche Bank
Laptops	3	Apple
Leisurewear	6	Hugo Boss
Mail-order companies	1	Amazon
Medium-sized cars	11	Volkswagen
Mobile network operators	1	Deutsche Telekom
Mobile phones	6	Apple
Personal computers	2	Apple
Scheduled flights	4	Deutsche Lufthansa
Sports shoes	3	Adidas
Television sets	4	Sony
Washing machines	3	Electrolux

Notes: The sum of firms exceeds the total number of firms in the sample, as firms can be categorized into multiple BRiC categories.

Most firms are categorized in the BRiC category of medium-sized cars (11), followed by mobile phones and leisurewear (6). Eight BRiC categories comprise only one firm. Nine firms can be categorized into two BRiC categories, and two firms can be categorized into three BRiC categories. In cases where a firm is classified into two or three BRiC categories, the BRiC for the firm is calculated as the mean across all categories.

Table 6 shows the descriptive statistics and correlations for the final data set, including 2011, 2014, and 2017. The mean excess return in the sample is 0.004 (SD = 0.081), and the mean brand equity is 0.101 (SD = 1.295).

Table 6: Descriptive Statistics and Correlations

Variable	Mean	SD	Min	Max
1. Excess return	0.004	0.081	-0.375	0.423
2. BRiC	3.636	0.511	2.291	4.632
3. Brand equity	0.101	1.295	-7.822	6.064
4. Capital intensity	-0.001	0.019	-0.076	0.063
5. Profit margin	0.004	0.034	-0.093	0.251
6. Leverage	0.000	0.057	-0.236	0.346
7. R&D intensity	-0.001	0.018	-0.186	0.033

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. Excess return	1.000						
2. BRiC	0.067**	1.000					
3. Brand equity	-0.030	-0.019	1.000				
4. Capital intensity	-0.044	-0.010	-0.044	1.000			
5. Profit margin	-0.062*	0.074**	0.073**	0.131***	1.000		
6. Leverage	0.042	0.114***	-0.037	-0.055*	-0.113***	1.000	
7. R&D intensity	-0.008	-0.169***	-0.053*	-0.177***	-0.687***	0.015	1.000

Notes: Variables (except excess returns and BRiC) represent unanticipated changes.
*p < 0.10, **p < 0.05, ***p < 0.01.

Applying a mean split using the yearly BRiC averages from Table 3 indicates no significant difference (t(1,535) = -0.603, p > 0.10)[15] in excess returns between low-BRiC firms (M = 0.002, SD = 0.076) and high-BRiC (M = 0.005, SD = 0.083). However, when analyzing raw brand equity data (not unanticipated changes), brand equity of high-BRiC firms (M = 14.645, SD = 12.992) is significantly higher (t(1,535) = -3.496, p < 0.001) than for low-BRiC firms (M = 12.114, SD = 13.895; see Table 7). This is in line with previous research indicating that in high-BRiC categories, firms' marketing actions translate into higher brand-related assets such as

[15] Levene's tests indicate that the homoscedasticity assumption holds (p > 0.05). Thus, mean difference tests for excess return and brand equity between low and high BRiC firms are based on t-tests for independent groups with equal variances. However, t-tests for independent groups with unequal variances yield the same results. I acknowledge that these t-tests only provide preliminary descriptive comparisons and do not account for repeated observations per firm and firms switching between low and high BRiC.

consumer trust in brands (Rajavi, Kushwaha, and Steenkamp 2019) or customer-based brand equity (Zhao et al. 2020).

Table 7: Descriptive Statistics by BRiC

	BRiC					BRiC			
	Low	**High**				**Low**	**High**		
No. of firms	22	41	t	p	No. of firms	22	41	t	p
Excess return					Brand equity [a]				
Mean	0.002	0.005	-0.603	> 0.10	**Mean**	**12.114**	**14.645**	**-3.496**	**< 0.001**
SD	0.076	0.083			SD	13.895	12.992		
Min	-0.356	-0.375			Min	-13.616	-13.513		
Max	0.292	0.423			Max	44.521	47.630		

Notes: The sum of low and high BRiC firms exceeds the total number of unique firms in the sample as the categorization of firms into low versus high BRiC can change between years due to differences in mean BRiC across years. Mean difference tests for excess returns and brand equity between low and high BRiC firms are based on t-tests for independent groups with equal variances. Significant differences are indicated in bold.
[a] The value for brand equity represents the raw data and not the unanticipated changes.

Note that the sum of the number of firms in low and high BRiC categories in Table 7 exceeds the total number of unique firms in the sample. This indicates that the categorization of firms into low or high BRiC can change over the years due to yearly differences in mean BRiC (see Table 3). In fact, 14 firms are categorized as both low and high BRiC depending on the year. For example, while Adidas is categorized as a low-BRiC firm in 2011 and 2014, it is classified as high-BRiC in 2017. Accordingly, it becomes necessary to investigate the moderating effect of BRiC accounting for changes in BRiC across years.

4.2 Model-Based Analyses

Table 8 shows the results of the main effects model and the full model with interaction effects. The model fit of the full model (R^2 = 0.270, adjusted R^2 = 0.263) is good and comparable to stock return response models in previous literature (e.g., Mizik and Jacobson 2008). The variance inflation factor (VIF), excluding the copula term, is below 10 (the highest VIF in the full model = 2.04).

Table 8: Results of the Main Models

	DV: Excess returns	
	Main effects model	**Full model**
Constant	-0.003 (0.004)	-0.002 (0.004)
Brand equity	-0.012 (0.008)	-0.012 (0.008)
BRiC	-0.001 (0.002)	-0.001 (0.002)
Brand equity × BRiC		**0.002 (0.001) ***
Capital intensity	**-0.005 (0.002) *****	**-0.005 (0.002) *****
Profit margin	-0.006 (0.004)	-0.006 (0.004)
Leverage	-0.002 (0.002)	-0.002 (0.002)
R&D intensity	-0.005 (0.007)	-0.005 (0.007)
Service	0.006 (0.004)	0.006 (0.004)
Copula	0.010 (0.008)	0.010 (0.008)
Market factor	**0.040 (0.003) *******	**0.040 (0.003) *******
Small-minus-big-factor	0.001 (0.003)	0.001 (0.003)
High-minus-low-factor	**-0.004 (0.002) ***	**-0.004 (0.002) ***
Momentum factor	**-0.004 (0.002) *****	**-0.004 (0.002) *****
Year-fixed effects	yes	yes
R^2 (adjusted R^2)	0.269 (0.263)	0.270 (0.263)
No. of observations	1,537	1,537

Notes: Results represent standardized coefficients. *p < 0.1, **p < 0.05, ***p < 0.01 (two-sided test). Significant effects are in bold. Clustered bootstrapped standard errors with 1,000 bootstrap resamples are in parentheses. For replicability, seed is randomly set to 100.

In line with previous research and the hypothesis, BRiC positively moderates the relationship between brand equity and stock returns (γ_2 = 0.002, p < 0.10). Thus, the findings of this research complement the moderating role of BRiC in the brand value chain. Interestingly, the main effects model results indicate a negative but insignificant association between brand equity and stock returns (γ_1 = -0.012, p > 0.10), which will be discussed later.

In terms of control variables, findings of the full model indicate a significant negative association of capital intensity (δ_1 = -0.005, p < 0.05) with stock returns. Additionally, the estimates of the risk factors suggest that stock returns move highly with the market (β_1 = 0.040, p < 0.01) and show a significant negative effect of the high-minus-low factor (β_3 = -0.004, p < 0.10) and the momentum factor (β_4 = -0.004, p < 0.05).

4.3 *Additional Analyses*

I performed several robustness checks to evaluate the reliability of the results in the main regression models. First, I estimated a model where the continuous BRiC variable is replaced by a dummy-coded BRiC variable using a median split. Second, following previous research, I included brand buzz as an additional control variable as a proxy for advertising effects (Malshe, Colicev, and Mittal 2020). Third, a model without the endogeneity correction using Gaussian copulas was performed. Finally, I re-estimate the full model using Newey and West's (1987) heteroscedasticity and autocorrelation consistent robust standard errors. The findings in Appendix F underline the robustness of the results of the main models (see Tables A6–A9). As shown in Table A6 in the Appendix, changing the operationalization of the BRiC moderator to a dummy variable does not influence the results. On the contrary, the interaction effect with BRiC is strengthened further, gaining significance. Similarly, including brand buzz as an additional control variable or removing the Gaussian copula correction from the model reinforces the findings of the main models (see Tables A7-A8 in the Appendix). Finally, Table A9 in the Appendix shows the unchanged results with Newey-West robust standard errors.

In addition to the robustness checks, I estimated a model using the BRiC values from the final year, specifically 2016, for all the years in the dataset (i.e., 2011, 2014, and 2017). This approach aimed to replicate common practice in marketing theory that measures BRiC only once and applies it to all years in the dataset (Nguyen and Feng 2021). Table A10 in the Appendix indicates that by doing so, the moderating effect of BRiC becomes insignificant. Therefore, measuring BRiC once for longitudinal analyses may underestimate its true effect, potentially leading to erroneous conclusions.

5 Discussion

5.1 *Summary and Discussion of Findings*

5.1.1 *Findings on BRiC*

The primary objective of this research is to provide a possible explanation for the high heterogeneity in the effect of brand-related assets on firm value (Edeling and Fischer 2016). Previous research indicates that brand equity's impact on firm value can differ across industries (e.g., Vomberg, Homburg, and Bornemann 2015). However, the underlying reason for these differences is still unclear. This research suggests that the differing relevance of brands for consumer decision-making across categories (BRiC) may explain the heterogeneity in the relationship between brand equity and firm value.

First, the current research findings show a significant positive moderating effect of BRiC (γ_2 = 0.002, $p < 0.10$) on the association between brand equity and firm value. Brand investments are valued more by the stock market in categories where the brand is highly relevant to consumers in their decision-making, leading to differences across firms in the brand equity-firm value link. To illustrate the significance of this moderating effect, consider the total market capitalization of all domestic companies listed in the Frankfurt Stock Exchange (XETRA) in 2011 (baseline year), which equaled €912.42 billion (Statista 2024). An increase in brand equity by one standard deviation alongside an increase in BRiC from low to high[16] would lead to total value growth of €2.48 billion on the stock exchange. Although the coefficient of the moderation effect of BRiC seems small, this simple calculation underlines its economic value.

Second, this research complements previous findings on BRiC's moderating role along the brand value chain (see Figure 1; Johnen and Schnittka 2020; Keller and Lehmann 2003; Nguyen

[16] Low versus high BRiC refers to one standard deviation below or above the mean. All other variables are set to their means. Dummy variables are set to 0. The baseline year is 2011.

and Feng 2021; Rajavi, Kushwaha, and Steenkamp 2019; Zhao et al. 2020). In line with past research emphasizing a positive moderating effect of BRiC between marketing activities and customer mindset metrics (Rajavi, Kushwaha, and Steenkamp 2019) and between customer mindset metrics and brand performance (Nguyen and Feng 2021; Zhao et al. 2020), I find a positive moderating effect of BRiC between customer mindset metrics and firm value. This finding is important for investigating the long-term and future-oriented impact of brands and complementing the brand's value creation process for firms (Edeling, Srinivasan, and Hanssens 2021; Rust et al. 2004). Additionally, this study provides guidance for researchers on the measurement of BRiC when analyzing several years of data. Findings of an additional analysis (see Table A10 in the Appendix) using BRiC values from the final year in the dataset for all years highlight that this approach can underestimate the true effect of BRiC and result in misleading conclusions. Thus, researchers using several years of data are well-advised to account for this measurement error in their analyses.

5.1.2 Findings on brand equity

Interestingly, I find a negative but insignificant effect of brand equity on firm value, which contrasts with the majority of findings in previous literature. Three reasons may explain this contradictory effect. First, the sample of firms in the current research is redistricted by the study design (49 unique firms). It is possible that firms in the current sample may already be operating at their optimal, i.e., firm-value-maximizing level, or are overinvested in brand assets. In that case, further improvements in brand equity may yield no effects or even negative returns on firm value (Edeling and Fischer 2016; Fischer and Wies 2024).

Second, some previous findings in marketing literature also show inconsistencies in brand equity's effect on firm value. For example, Mizik and Jacobson (2008) emphasize that only specific brand equity dimensions significantly affect firm value, while others display a null effect. Some insignificant effects also show a negative sign in line with the current research findings. Similarly, Luo, Raithel, and Wiles (2013) find a long-term but no significant immediate effect of brand equity on firm value.

Third, methodological differences between studies, such as data source, data handling, observation period, or model specification, may have led to different findings (Edeling and Fischer 2016). Compared to previous studies, this research includes more recent data (up to 2017) at higher frequencies (i.e., monthly versus yearly data) and accounts for potential endogeneity concerns related to brand equity (see also Table 1 for a comparison between studies). According to previous research, investors value unanticipated changes in brand quality less when a concurrent decline in earnings is observed (Bharadwaj, Tuli, and Bonfrer 2011). Thus, on a monthly level, investors might perceive the unanticipated increase in brand equity as an investment that has a short-term negative effect on the firm's profitability, without recognizing the long-term benefits of building strong brands. Finally, when excluding the endogeneity correction using the Gaussian copula term in robustness checks (see Table A8 in the Appendix), the effect of brand equity becomes more positive, indicating an upward bias of not accounting for endogeneity. This is in line with previous meta-analytical research demonstrating an upward bias in estimates of advertising elasticities when endogeneity is not accounted for (Edeling and Fischer 2016).

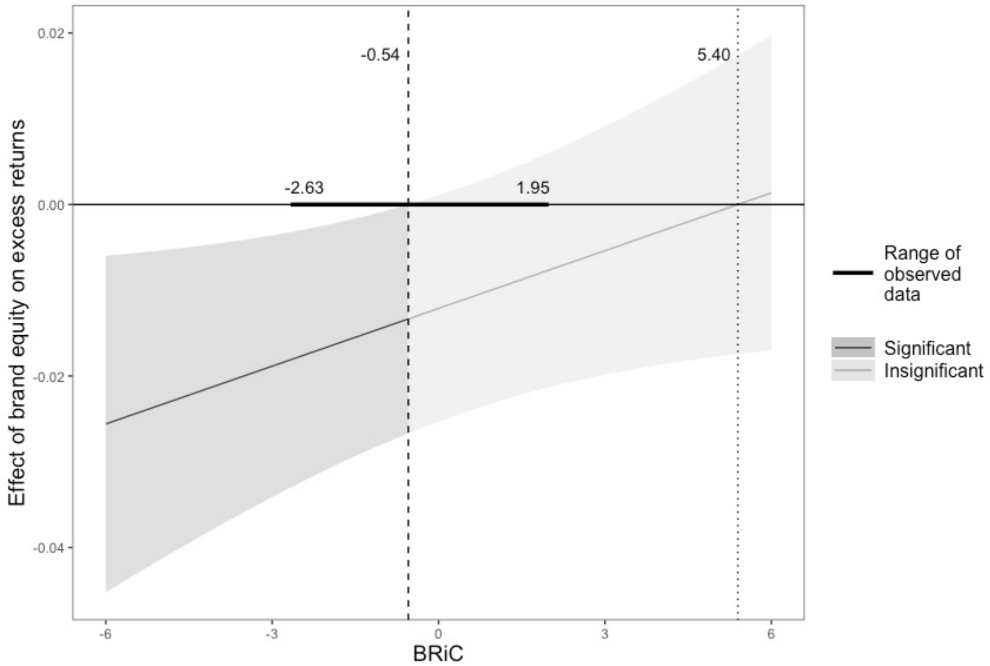
5.1.3 Further considerations

Given the insignificant negative main effect of brand equity and the significant positive moderating effect of BRiC, the following two questions arise:

1. For which values of BRiC does the effect of brand equity on excess returns become *significant*?
2. For which values of BRiC does the effect of brand equity on excess returns become *positive*?

Figure 3 displays the Johnson-Neyman plot (Johnson and Neyman 1936), indicating at which BRiC values the effect of brand equity on excess returns becomes significant at a p-value of 0.10.

Figure 3: Conditional Effect of Brand Equity on Excess Returns as a Function of BRiC



Notes: The solid dark and light grey lines depict the estimated slope of brand equity on excess returns across values of BRiC, while the surrounding dark and light grey areas represent the corresponding 90% confidence intervals. The bold black line along the x-axis shows the range of observed BRiC values (in standard deviation units). The vertical dashed black line indicates the level of BRiC where the effect of brand equity on excess returns becomes insignificant. The vertical dotted black line indicates the level of BRiC where the effect of brand equity on excess returns turns positive.

The Johnson-Neyman plot reveals a significant negative effect of brand equity on excess returns for BRiC values less than 0.54 standard deviations below the mean BRiC. For BRiC values above this threshold, the effect of brand equity on excess returns becomes more positive but insignificant. This finding supports the notion that the brand equity's impact on firm value depends on BRiC, which may explain the heterogeneous findings in the literature. Depending on the construction of the sample of firms in the analysis, the findings of brand equity on firm value may differ. Beyond 5.40 standard deviations above the mean BRiC value in the sample, the effect of brand equity on excess returns even turns positive. Although such strong deviations from the mean BRiC are not observed in the current dataset (see solid black line in Figure 3), high variations in the effect of brand equity across categories or time are possible. For example, the maximum cross-sectional difference in BRiC observed between the 30 categories in the current dataset in 2010 is 1.97 scale points, which equals 3.86 standard deviations from the mean (see Table 2). Similarly, the maximum within-firm change in BRiC over time amounts to 3.19 standard deviations from the mean for the category of express delivery services, which increased by 1.63 scale points from 2006 to 2019. Consequently, the effect of brand equity on stock returns for a firm in the express delivery service category (e.g., DHL) can change by approximately 0.007, which is substantial given that the average excess return in the sample is 0.004. Thus, these findings bear important managerial implications.

5.2 Managerial Implications

The current research findings demonstrate that the effect of brand equity on firm value is conditional on the relevance of brands for consumers (i.e., BRiC), which differs across categories (Fischer, Völckner, and Sattler 2010). In high-BRiC categories, investors value brand-building investments more, even in the short run. Thus, firms operating in high-BRiC categories that strongly differentiate on brand equity (e.g., beer) may invest more in brand-building without fearing adverse investor reactions. In contrast, in categories where BRiC is low, investments in brand equity can yield negative stock returns. Therefore, firms in low-BRiC categories such as contractual service industries (e.g., electricity providers), where customer equity can be more easily measured and managed, are well-advised to focus on creating valuable customer relationships. Firms operating in several categories simultaneously should consider that the stock market does not value brand-building activities equally in all categories and allocate their brand investments accordingly.

Additionally, the value-creating potential of brands can change over time due to changes in BRiC, especially in the wake of severe negative publicity in a category (Karagür 2025). For example, following the Volkswagen emission scandal in 2015 (BBC 2015), BRiC in the medium-sized cars category increased by over 22% (Karagür 2025). In such cases, firms may consider investing in brand building to influence consumer choices positively. At the same time, the current research suggests that when BRiC increases, managers do not have to fear negative investor reactions to brand-building investments. Depending on how drastically the negative event impacts the category and BRiC, brand equity investments can even grow firm value (see Figure 3). This consideration can further encourage managers to engage in brand-building activities in adverse times.

Overall, this research suggests that managers should periodically measure BRiC to make informed decisions and anticipate investor reactions to brand-building activities. The scale developed by Fischer, Völckner, and Sattler (2010) can provide a cost-efficient means for measuring BRiC, which firms can easily apply.

5.3 Limitations and Directions for Future Research

Although this research is the first to quantify the moderating impact of BRiC on firm value, it has some limitations. These limitations can guide future research. First, as this research aimed to include several years of BRiC data, the sample consists of only 49 companies from 22 unique categories. Compared to previous literature (see Table 1), this sample of firms might have been limited, resulting in surprising findings regarding the main effect of brand equity. Further research could extend the number of companies and categories included in the sample to increase the generalizability of the results. Second, previous research emphasizes that BRiC also changes across countries (Fischer, Völckner, and Sattler 2010). Today, firms operate globally, and the increasing number of online brokerage platforms facilitates global retail trading (Baker 2024). Thus, future research could focus on a cross-sectional analysis and consider measuring BRiC in different countries. Lastly, this research is built on monthly data, which differs from previous research using yearly data. Therefore, the insignificant negative effect of brand equity on stock returns in the current research might reflect a short-term perspective of the stock market. Considerations regarding the persistence of the changes in brand equity may influence stock market reactions. Future research could examine this by applying a higher-level temporal aggregation similar to previous studies using yearly data (e.g., Mizik 2014)[17].

[17] Note that in the current study, the limited number of firms does not allow for an impactful analysis on the yearly level.

References Paper 2

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Appendix Paper 2

In this Appendix, I provide the following information:

1) Appendix A: Details on the YouGov Data
2) Appendix B: Details on the BRiC Data
3) Appendix C: Construction of the Final Sample
4) Appendix D: Rankings in BRiC Across Categories and Waves
5) Appendix E: Results of Nonnormality Tests
6) Appendix F: Results of Additional Analyses

Appendix A: Details on the YouGov Data

YouGov is a global market research company that collects daily brand metrics using an online panel of over 2,500 consumers. In Germany, YouGov monitors over 1,326 brands from 37 different industry sectors (status July 2020) and thus offers representative measures that have been applied extensively in previous research (e.g., Luo, Raithel, and Wiles 2013; Stäbler and Fischer 2020).

I measure brand equity in this research using YouGov's BrandIndex, which consists of six dimensions: impression, satisfaction, quality, value, reputation, and recommendation. Each dimension is collected using positive and negative statements, and respondents must indicate which brands they categorize as positive or negative. For example, when asked about the general impression dimension, respondents select all brands they agree with on the positive statement (Which of the following brands do you have a generally *positive* feeling about?) and on the negative statement (Which of the following brands do you have a generally *negative* feeling about?). The remaining five indicators follow the same procedure (see Table A1 for exact questions). The BrandIndex score is calculated as the average of all six dimensions and ranges from -100 to +100. To construct the brand equity measure, I downloaded the daily values for all brands and aggregated them to monthly scores. When brands are tracked twice in YouGov (e.g., in different sectors), I take the average of both values.

Table A1: Questions Used by YouGov

YouGov metric	Questions
Impression	Which of the following brands do you have a generally *positive/negative* feeling about?
Satisfaction	Which of the following brands would you say that you are a *satisfied/dissatisfied* customer of?
Quality	Which of the following brands do you think represents *good/poor* quality?
Value	Which of the following brands do you think *represents good/poor value for money*?
Reputation	Imagine you were looking for a job (or advising a friend looking for a job). Which of the following companies would you be *proud/embarrassed* to work for?
Recommendation	Which of the following brands would you *recommend*/tell a friend to *avoid*?

Appendix B: Details on the BRiC Data

An external market research provider collected consumer perceptions of BRiC in 30 categories covering FMCG, services, durables, and retail in Germany over five waves (2006, 2010, 2013, 2016, and 2019). Respondents differed in each wave, which resulted in a repeated cross-sectional design. After applying specific sample selection criteria, such as accounting for uniform response style (see Karagür 2025 for details), the final sample included 13,991 observations from 5,053 respondents. The BRiC scale proposed by Fischer, Völckner, and Sattler (2010) consists of the following four items translated from German.

Table A2: Items of the BRiC Scale

Item	Item description
BRiC 1	When I purchase a product in the given category, the brand plays –compared to other things– an important role.
BRiC 2	When purchasing, I focus mainly on the brand.
BRiC 3	To me, it is important to purchase a brand name product.
BRiC 4	The brand plays a significant role as to how satisfied I am with the product.

To verify the proposed scale, I performed an exploratory factor analysis using both Promax and Varimax rotation for the pooled dataset across all waves (see Table A3). Both analyses yielded the same results, indicating a one-factor solution with all eigenvalues greater than one. Similarly, Cronbach's alpha is 0.94, indicating good internal validity. Thus, I take the average of the respective items to construct the BRiC scale.

Table A3: Factor Analysis for the Pooled Data Using Promax and Varimax Rotation

	Promax (3.139)	Varimax (3.139)
BRiC 1	0.905	0.905
BRiC 2	0.920	0.920
BRiC 3	0.885	0.885
BRiC 4	0.831	0.831

Notes: The eigenvalues (greater than 1) are reported in parentheses.

Appendix C: Construction of the Final Sample

To construct the final data set, brands in YouGov must be categorized into the BRiC categories. Therefore, three coders (including the author) independently categorized all 1,326 brands monitored by YouGov in Germany into the 30 BRiC categories. The overall intercoder agreement was over 98%. If all coders agreed on categorizing a brand into a specific category, the brand was assigned class A; brands only categorized by two coders were class B, and brands only categorized by one coder were classified as class C. While all class A brands were classified into the respective categories, the inclusion of class B and class C brands was decided after discussions. Only 28 of the 30 BRiC categories could be matched with brands from YouGov. This led to a final categorization of 456 brands in total and 393 unique brands into at least one of the 28 BRiC categories (see Table A4).

In the next step, a student research assistant researched the parent company of the 393 unique brands, indicated whether the parent company owns several brands or follows a corporate branding strategy, and specified whether the parent company was publicly listed on any global stock exchange. This led to a selection of 64 brands. Out of these 64 brands, only 53 were publicly listed corporate brands included in COMPUSTAT from 2008 to 2019. As the common observation period of all data sets is 2009 to 2019, and the BRiC data needs to be lagged by one year to mitigate endogeneity concerns, the final data set covers 2011, 2014, and 2017. Thus, in the final step, only brands included in all data sets in the relevant years remained. This led to 1,537 firm-month observations by 49 unique firms.

Table A4: Number of Brands in Each BRiC Category

Category	Number of brands
Bank accounts	17
Beer	28
Car insurances	28
Car repair shops	6
Department stores	7[a]
Designer sunglasses	6
Detergent	24
Discounter	9
Drug stores	3
Electricity providers	18
Express delivery services	11
Fast-food restaurants	11
Gaming software	5
Hardware stores	7
Headache tablets	6
Health insurances	20
Investment funds	5
Laptops	14
Leisurewear	48
Mail-order companies	54
Medium-sized cars	23
Mobile network operators	18
Mobile phones	18
Personal computers	8
Scheduled flights	18
Sport shoes	10
Television sets	12
Washing machines	22
Total	456
Mean	16.29
SD	12.21

Notes: At the time of data collection, department stores included 7 brands. However, in previous years, one department store brand, which is a merger of two department stores was tracked as two separate brands. Thus, the number of brands in department stores category can vary across years.

Appendix D: Rankings in BRiC Across Categories and Waves

Table A5: Rankings of BRiC Across Categories and Waves

Rank	2006		2010		2013		2016		2019	
1	Beer	4.72	Beer	4.26	Washing machines	4.36	Medium-sized cars	4.63	Cigarettes	4.56
2	Cigarettes	4.62	Laptops	4.06	Bank accounts	3.97	Cigarettes	4.47	Mobile phones	4.35
3	Mobile phones	4.62	Cigarettes	4.04	Medium-sized cars	3.79	Laptops	4.38	Medium-sized cars	4.30
4	Designer sunglasses	4.19	Mobile phones	3.87	Headache tablets	3.79	Beer	4.36	Beer	4.26
5	Television sets	4.19	Medium-sized cars	3.74	Laptops	3.75	Personal computers	4.34	Express delivery services	4.26
6	Laptops	4.17	Personal computers	3.73	Personal computers	3.69	Mobile phones	4.31	Laptops	4.20
7	Medium-sized cars	4.11	Investment funds	3.71	Television sets	3.67	Investment funds	4.22	Television sets	4.11
8	Headache tablets	4.08	Designer sunglasses	3.68	Beer	3.65	Sports shoes	4.18	Washing machines	4.04
9	Washing machines	4.06	Washing machines	3.52	Mobile phones	3.62	Washing machines	3.95	Investment funds	3.90
10	Fast-food restaurants	3.89	Sports shoes	3.52	Mobile network operators	3.54	Designer sunglasses	3.92	Designer sunglasses	3.90
11	Scheduled flights	3.66	Fast-food restaurants	3.49	Sports shoes	3.51	Television sets	3.84	Mail-order companies	3.87
12	Investment funds	3.64	Bank accounts	3.48	Fast-food restaurants	3.47	Express delivery services	3.77	Sports shoes	3.84
13	Sports shoes	3.64	Headache tablets	3.42	Detergents	3.46	Scheduled flights	3.75	Detergents	3.82
14	Personal computers	3.52	Television sets	3.38	Health insurances	3.38	Fast-food restaurants	3.61	Scheduled flights	3.81
15	Mail-order companies	3.42	Detergents	3.38	Scheduled flights	3.36	Leisurewear	3.60	Health insurances	3.74

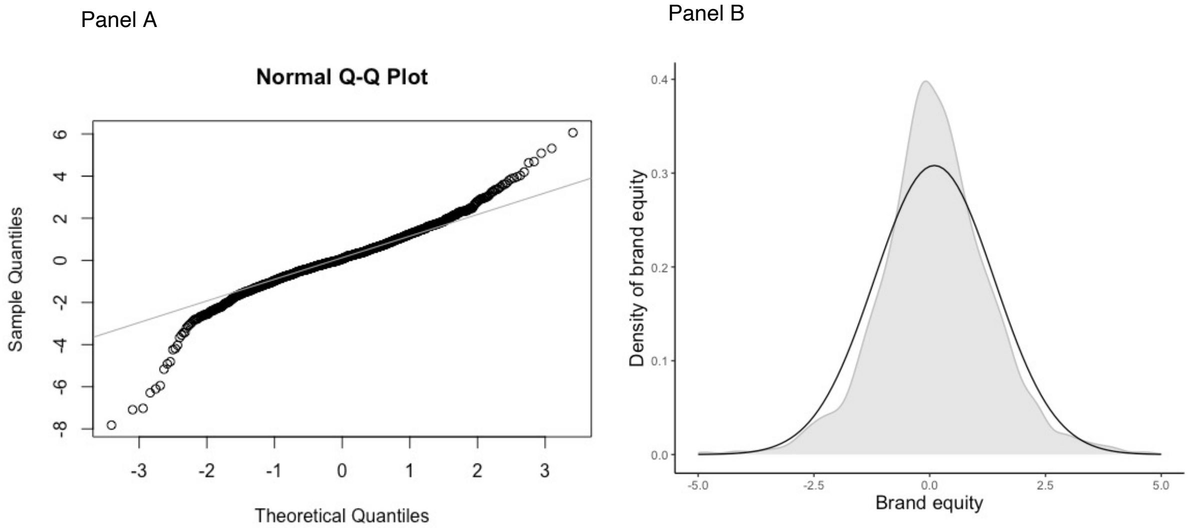
Table A5: Rankings of BRiC Across Categories and Waves (Continued)

Rank	2006		2010		2013		2016		2019	
16	Bank accounts	3.26	Mail-order companies	3.37	Hardware stores	3.31	Car insurances	3.59	Bank accounts	3.71
17	Leisurewear	3.17	Scheduled flights	3.17	Cigarettes	3.30	Mail-order companies	3.58	Car insurances	3.68
18	Department stores	3.16	Mobile network operators	3.06	Department stores	3.25	Headache tablets	3.53	Mobile network operators	3.60
19	Car repair shops	3.13	Car repair shops	3.01	Car insurances	3.23	Health insurances	3.46	Headache tablets	3.58
20	Detergents	3.12	Express delivery services	3.00	Investment funds	3.22	Bank accounts	3.44	Personal computers	3.56
21	Drugstores	3.07	Leisurewear	2.98	Electricity providers	3.21	Detergents	3.37	Fast-food restaurants	3.53
22	Mobile network operators	3.03	Health insurances	2.96	Mail-order companies	3.16	Drugstores	3.36	Car repair shops	3.37
23	Discounter	2.99	Discounter	2.82	Designer sunglasses	3.13	Department stores	3.32	Department stores	3.26
24	Hardware stores	2.97	Gaming software	2.79	Gaming software	3.12	Gaming software	3.31	Gaming software	3.23
25	Car insurances	2.86	Car insurances	2.71	Paper tissues	3.10	Car repair shops	3.24	Hardware stores	3.19
26	Paper tissues	2.85	Department stores	2.67	Discounter	3.05	Mobile network operators	3.11	Electricity providers	3.17
27	Health insurances	2.70	Paper tissues	2.65	Drugstores	2.94	Discounter	3.07	Leisurewear	3.16
28	Express delivery services	2.63	Drugstores	2.59	Express delivery services	2.93	Hardware stores	2.95	Drugstores	3.07
29	Gaming software	2.33	Hardware stores	2.39	Car repair shops	2.79	Electricity providers	2.89	Discounter	2.93
30	Electricity providers	1.91	Electricity providers	2.29	Leisurewear	2.65	Paper tissues	2.80	Paper tissues	2.51

Appendix E: Results of Nonnormality Tests

The results of both the Anderson–Darling test ($A^2 = 9.689$, $p < 0.001$) and Cramer-van Mieses test ($W^2 = 1.579$, $p < 0.0001$) confirm the nonnormality of the potentially endogenous variable brand equity. The density and quantile-quantile (QQ) plots also support the nonnormality assumption (Figure A1).

Figure A1: Visual Non-Normality Checks of Brand Equity



Notes: Panel A shows the QQ-plot of the residuals of brand equity. The grey line represents the theoretical quantiles of a normal distribution. Data points (in black) that deviate from the grey line suggest that the residuals are not normally distributed. Panel B illustrates the density plot of brand equity. The black line shows a normal distribution derived from brand equity's mean and standard deviation. The grey area displays the actual density of the variable, which indicates nonnormality.

Appendix F: Results of Additional Analyses

To underline the robustness of the main model results, I performed several robustness checks. First, I estimated a model with a dummy BRiC variable using a median split ($BRiC_{median}$ = 3.688) to replace the continuous BRiC variable. As evident in Table A6, the results of the main models remain unchanged. The moderating effect of BRiC becomes even stronger (coefficient = 0.008, $p < 0.05$) following a dichotomous variable categorization.

Table A6: Results of Models with BRiC Dummy

	DV: Excess returns	
	Main effects model	**Full model**
Constant	-0.002 (0.005)	-0.002 (0.005)
Brand equity	-0.012 (0.008)	-0.015 (0.009)
BRiC_dummy [a]	-0.001 (0.005)	-0.001 (0.005)
Brand equity × BRiC_dummy [a]		**0.008 (0.003) ****
Capital intensity	**-0.005 (0.002) ****	**-0.005 (0.002) ****
Profit margin	-0.006 (0.004)	-0.006 (0.004)
Leverage	-0.002 (0.002)	-0.002 (0.002)
R&D intensity	-0.005 (0.007)	-0.004 (0.007)
Service	**0.007 (0.004) ***	**0.007 (0.004) ***
Copula	0.010 (0.008)	0.008 (0.008)
Market factor	**0.040 (0.003) *****	**0.040 (0.003) *****
Small-minus-big-factor	0.001 (0.003)	0.001 (0.003)
High-minus-low-factor	**-0.004 (0.002) ***	**-0.004 (0.002) ***
Momentum factor	**-0.004 (0.002) ****	**-0.004 (0.002) ****
Year-fixed effects	yes	Yes
R^2 (adjusted R^2)	0.269 (0.263)	0.272 (0.265)
No. of observations	1,537	1,537

Notes: Results represent standardized coefficients. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$ (two-sided test). Significant effects are in bold. Clustered bootstrapped standard errors with 1,000 bootstrap resamples are in parentheses. For replicability, seed is randomly set to 100. [a] BRiC_dummy = 1 if BRiC > $BRiC_{median}$, 0 otherwise.

Second, a model that includes brand buzz as a proxy for advertising effects (Malshe, Colicev, and Mittal 2020) is estimated. To operationalize brand buzz, I used YouGov's buzz metric, which captures the proportion of respondents who have heard anything positive or negative about a brand over the past two weeks and ranges from -100 to +100. A positive score indicates positive buzz, and a negative score represents negative buzz. Table A7 indicates that the significant positive moderation effect of BRiC holds after including brand buzz in the model. In addition, the association of brand equity and excess returns becomes weaker, albeit still insignificant, indicating that brand buzz captures some of brand equity's effect.

Table A7: Results of Models with Brand Buzz

	DV: Excess returns	
	Main effects model	**Full model**
Constant	-0.002 (0.004)	-0.002 (0.004)
Brand equity	-0.008 (0.009)	-0.007 (0.010)
BRiC	-0.001 (0.002)	-0.001 (0.002)
Brand equity × BRiC		**0.002 (0.001) ***
Brand buzz	-0.002 (0.003)	-0.003 (0.003)
Capital intensity	**-0.005 (0.002) ****	**-0.005 (0.002) ****
Profit margin	-0.006 (0.004)	-0.006 (0.004)
Leverage	-0.002 (0.002)	-0.002 (0.002)
R&D intensity	-0.005 (0.007)	-0.005 (0.007)
Service	0.007 (0.004)	0.007 (0.004)
Copula	0.006 (0.009)	0.006 (0.009)
Market factor	**0.040 (0.003) *****	**0.040 (0.003) *****
Small-minus-big-factor	0.001 (0.003)	0.001 (0.003)
High-minus-low-factor	**-0.004 (0.002) ***	**-0.004 (0.002) ***
Momentum factor	**-0.005 (0.002) ****	**-0.005 (0.002) ****
Year-fixed effects	yes	yes
R^2 (adjusted R^2)	0.270 (0.263)	0.271 (0.263)
No. of observations	1,537	1,537

Notes: Results represent standardized coefficients. *p < 0.1, **p < 0.05, ***p < 0.01 (two-sided test). Significant effects are in bold. Clustered bootstrapped standard errors with 1,000 bootstrap resamples are in parentheses. For replicability, seed is randomly set to 100.

Third, a model without the copula correction for brand equity is estimated. The results (see Table A8) support the findings in the main model regarding the positive moderating effect of BRiC. Note that the effect size of the main effect of brand equity is smaller (more positive) (coefficient = -0.003, p > 0.10) when the Gaussian copula is not included compared to the model with the endogeneity correction using the Gaussian copula (γ_1 = -0.012, p > 0.10). This finding indicates an upward bias in the estimate of brand equity when endogeneity is not corrected for.

Table A8: Results of Models Without Copula Term

	DV: Excess returns	
	Main effects model	**Full model**
Constant	-0.002 (0.004)	-0.002 (0.004)
Brand equity	-0.003 (0.002)	-0.003 (0.002)
BRiC	-0.001 (0.002)	-0.001 (0.002)
Brand equity × BRiC		**0.002** (**0.001**) *
Capital intensity	**-0.005** (**0.002**) **	**-0.005** (**0.002**) **
Profit margin	-0.006 (0.004)	-0.006 (0.004)
Leverage	-0.002 (0.002)	-0.002 (0.002)
R&D intensity	-0.005 (0.007)	-0.005 (0.007)
Service	0.007 (0.004)	0.007 (0.004)
Market factor	**0.040** (**0.003**) ***	**0.040** (**0.003**) ***
Small-minus-big-factor	0.001 (0.003)	0.001 (0.003)
High-minus-low-factor	**-0.004** (**0.002**) *	**-0.004** (**0.002**) *
Momentum factor	**-0.004** (**0.002**) **	**-0.004** (**0.002**) **
Year-fixed effects	yes	yes
R^2 (adjusted R^2)	0.269 (0.263)	0.270 (0.263)
No. of observations	1,537	1,537

Notes: Results represent standardized coefficients. *p < 0.1, **p < 0.05, ***p < 0.01 (two-sided test). Significant effects are in bold. Clustered bootstrapped standard errors with 1,000 bootstrap resamples are in parentheses. For replicability, seed is randomly set to 100.

Finally, I re-estimated the main model with interactions using Newey and West's (1987) heteroscedasticity and autocorrelation-consistent robust standard errors. As evident in Table A9, the results remain unchanged.

Table A9: Results of Models With Newey-West Standard Errors

	DV: Excess returns	
	Main effects model	**Full model**
Constant	-0.003 (0.004)	-0.002 (0.004)
Brand equity	-0.012 (0.008)	-0.012 (0.008)
BRiC	-0.001 (0.002)	-0.001 (0.002)
Brand equity × BRiC		**0.002 (0.001) ***
Capital intensity	**-0.005 (0.002) ****	**-0.005 (0.002) ****
Profit margin	**-0.006 (0.004) ***	**-0.006 (0.003) ***
Leverage	-0.002 (0.002)	-0.002 (0.002)
R&D intensity	-0.005 (0.003)	-0.005 (0.003)
Service	0.006 (0.005)	0.006 (0.004)
Copula	0.010 (0.008)	0.010 (0.008)
Market factor	**0.040 (0.002) *****	**0.040 (0.003) *****
Small-minus-big-factor	0.001 (0.002)	0.001 (0.002)
High-minus-low-factor	**-0.004 (0.002) ****	**-0.004 (0.002) ****
Momentum factor	**-0.004 (0.002) ****	**-0.004 (0.002) ****
Year-fixed effects	yes	yes
R^2 (adjusted R^2)	0.269 (0.263)	0.270 (0.263)
No. of observations	1,537	1,537

Notes: Results represent standardized coefficients. *p < 0.1, **p < 0.05, ***p < 0.01 (two-sided test). Significant effects are in bold. Newey-West standard errors are in parentheses.

Research so far measures BRiC once and applies it to all the years in their dataset (Nguyen and Feng 2021). To evaluate whether this approach raises any concerns regarding the validity of the findings, I estimated a model using the BRiC values from the final year, specifically 2016, and applied these values to all years in the dataset (2011, 2014, and 2017). Since one company in the final dataset was not included in 2017, I re-estimated the main model with 48 companies and compared the results to the model that used 2016 BRiC values. Table A10 shows that the moderating effect of BRiC becomes insignificant when applying the 2016 BRiC values to the entire observation period (2016 BRiC model). Therefore, measuring BRiC once for longitudinal analyses could lead to misleading conclusions by underestimating the true effect of BRiC.

Table A10: Results of Models Using 2016 BRiC Values

	DV: Excess returns	
	Main model	**2016 BRiC model**
Constant	-0.002 (0.004)	-0.002 (0.004)
Brand equity	-0.013 (0.008)	-0.012 (0.008)
BRiC	-0.001 (0.002)	0.000 (0.002)
Brand equity × BRiC	**0.002 (0.001) ***	0.002 (0.002)
Capital intensity	**-0.004 (0.002) ***	**-0.004 (0.002) ***
Profit margin	-0.007 (0.004)	-0.007 (0.004)
Leverage	-0.002 (0.003)	-0.002 (0.003)
R&D intensity	-0.005 (0.007)	-0.005 (0.007)
Service	0.007 (0.004)	**0.007 (0.004) ***
Copula	0.011 (0.008)	0.010 (0.008)
Market factor	**0.040 (0.003) *****	**0.040 (0.003) *****
Small-minus-big-factor	0.001 (0.003)	0.001 (0.003)
High-minus-low-factor	**-0.004 (0.002) ***	**-0.004 (0.002) ***
Momentum factor	**-0.004 (0.002) *****	**-0.004 (0.002) *****
Year-fixed effects	yes	yes
R^2 (adjusted R^2)	0.269 (0.262)	0.269 (0.261)
No. of observations	1,522	1,522

Notes: Results represent standardized coefficients. *p < 0.1, **p < 0.05, ***p < 0.01 (two-sided test). Significant effects are in bold. Clustered bootstrapped standard errors with 1,000 bootstrap resamples are in parentheses. For replicability, seed is randomly set to 100.

References Appendix Paper 2

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PAPER 3: STRONGER TOGETHER – THE COMPLEMENTARY EFFECT OF REAL-TIME AND SURVEY-BASED BRAND MEASURES ON FIRM VALUE

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ABSTRACT[18]

Traditional survey-based brand measures are costly to collect and thus mostly available at a timely aggregated level (e.g., quarterly or yearly). This raises the pressure to complement or even replace survey-based brand measures with more granular, dynamic, and cost-efficient real-time brand measures. In response, recent work has developed the brand reputation tracker, a real-time brand measure that builds on consumers' social media posts about brands. Previous research findings support the relevance of brand-related social media posts on firm value. But how do social media-based real-time brand measures relate to traditional survey-based brand measures? This article compares a popular survey-based brand measure to the brand reputation tracker. A low and negative correlation between both brand measures indicates that they capture complementary components of consumer perceptions. Building on 4,290 brand-week observations, the results of vector autoregressive models additionally show that the real-time and survey-based brand measures fulfill complementary roles in explaining firm value. Combining both brand measures significantly increases the explanatory power of the model. This complementary effect is especially high for manufacturing brands. In contrast, the relevance of survey-based brand measures is stronger for service brands. These findings offer valuable insights for marketing managers on selecting brand measures.

Keywords: Brand management, brand metrics, purchase funnel, vector autoregressive models, firm value

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1 Introduction

"[…] the power of a brand lies in what customers have learned, felt, seen, heard, etc about the brand […]". – Kevin Lane Keller (2003, p. 9).

Measuring how consumers think and feel about brands (customer-based brand equity [CBBE])[19] has long been a central theme in marketing theory and practice. The two most prominent concepts in marketing theory to conceptualize and measure consumer brand perceptions are Keller's (1993) CBBE framework and Aaker's (1996) Brand Equity Ten. Over the years, many commercial providers measuring consumer brand perceptions have also emerged, but they are mostly at a non-granular level (e.g., quarterly or annually) and built on large-scale consumer surveys. One caveat of survey-based brand measures is that they "[…] move slowly over time and are insensitive to short-term marketing actions" (Marketing Science Institute 2022, p.6). This notion is underlined in recent work by Pauwels and van Ewijk (2020), who argue that survey-based metrics (e.g., awareness) capture enduring attitudes while online behavior metrics (e.g., website visits) represent contextual interest. Consequently, the urge to complement or even substitute survey-based brand measures with other metrics that capture consumer brand perceptions in real-time has grown stronger in recent years (Marketing Science Institute 2022). Such real-time measures can be based on social media data, which is becoming increasingly important as an environment for brand-related consumer conversations that impact firm performance (Fossen and Schweidel 2019; Hewett et al. 2016). A recent example is the GameStop short squeeze on January 28, 2021, which caused the U.S. video game retailer's stock to increase by over 1800% of its initial value following a coordinated buying of users on Reddit (Davies 2021). Thus, it is not surprising that firms are shifting towards social media to monitor consumer brand perceptions, with the social media analytics market size projected to

[19] Note that this research focuses on measuring consumer perceptions, i.e., customer-based brand equity (CBBE). Thus, in the following, brand measures refer to measures of CBBE.

grow from \$13.47 billion in 2024 to \$61.95 billion by 2032 (Fortune Business Insights 2025). Companies can either rely on social media data and commercial analytics tools from external providers (e.g., Sprout Social) or utilize software solutions such as Linguistic Inquiry and Word Count (LIWC; Fortune Business Insights 2025; Kübler, Colicev, and Pauwels 2020). In addition, Rust et al. (2021) have recently developed a brand reputation tracker using social media data. The main advantages of the brand reputation tracker over other non-theory-driven commercial approaches are its justification based on marketing theory and the actionability of its sub-drivers (Rust et al. 2021). Specifically, the brand reputation tracker builds on the three drivers of the customer equity framework: value, brand, and relationship, which are further decomposed into sub-drivers, increasing the actionability of the tracker (Rust, Zetihaml, and Lemon 2000; Rust et al. 2021). Hence, this research refers to the brand reputation tracker as the real-time brand measure, which provides publicly available brand perceptions for 100 global brands from July 1, 2016, to December 31, 2018, on a weekly or quarterly level.

Attempts to replicate and extend the brand reputation tracker (Cadili 2022) or demonstrate its financial accountability (Rust et al. 2021) have already been conducted, demonstrating the high usability of the tracker. However, to the best of my knowledge, no research so far has compared the brand reputation tracker to traditional survey-based brand measures and assessed their isolated and combined effects on firm performance. Although one might assume a high correlation and thus low complementary effects between different types of brand measures, conceptual and methodological differences and existing research findings suggest otherwise. For example, survey-based methods only consider the consumer perspective, whereas the brand reputation tracker encompasses a broader range of stakeholders, including current and future consumers, employees, and investors (Rust et al. 2021). Additionally, previous research reports low correlations between survey-based attitude measures and online behavior metrics, such as website visits, and highlights the relevance of survey-based measures in explaining firm performance (Colicev et al. 2018; Pauwels and van Ewijk 2020).

Accordingly, existing literature emphasizes a complementary effect of survey-based measures and online metrics (Colicev et al. 2018; Kübler, Colicev, and Pauwels 2020; Pauwels and van Ewijk 2020). They either combine survey-based consumer mindset metrics (e.g., brand awareness) with online consumer behavior metrics (e.g., website visits; Pauwels and van Ewijk 2020) or social media data (e.g., likes, volume, sentiment; Colicev et al. 2018; Kübler, Colicev, and Pauwels 2020). While the former addresses the question of whether online consumer *behavior* metrics can complement survey-based *attitude* measures, the latter studies compare the effects of different social media-based metrics on survey-based *attitude* measures. To the best of my knowledge, no research has explicitly investigated the relationship between social media-based real-time *attitude* brand measures and traditional survey-based *attitude* brand measures. This research aims to close this gap by addressing the following research questions:

1. How are (social media-based) real-time brand measures[20] associated with survey-based brand measures across brands?
2. What is the effect of each brand measure, separately and combined, in explaining firm value?
3. When are the separate and complementary effects of both brand measures stronger or weaker?

To address these research questions, I compare the brand reputation tracker to one of the most popular commercial survey-based brand measures, YouGov's BrandIndex. Compared to other survey-based brand measures, YouGov's BrandIndex measure is available at a high granularity, i.e., daily[21], and is thus becoming increasingly popular in marketing research (e.g.,

[20] In the following, I will use the term real-time brand measure(s) interchangeable to social media-based real-time brand measure(s).
[21] Even though YouGov's BrandIndex measure is available at a high timely granularity, real-time brand measures outperform the BrandIndex by theoretically being able to capture brand perceptions in real-time, e.g., hourly.

Colicev et al. 2018; Kübler, Colicev, and Pauwels 2020; Luo, Raithel, and Wiles 2013; Stäbler and Fischer 2020). Following Aaker's criteria for evaluating good brand measures (Aaker 1996), this research analyzes the relationship and strength of both brand measures in three steps. First, I investigate the correlation between the brand measures and their ability to reflect major internal and external brand events (e.g., product introduction and negative publicity). Subsequently, both brand measures are compared in terms of their strength to explain the variation in firm value across brands and industries. Existing marketing-finance literature highlights firm value as an important future-oriented metric of firm performance (Edeling and Fischer 2016; Rappaport 1998) and demonstrates a positive relationship with consumer brand perceptions (e.g., Mizik and Jacobson 2008). Yet the question of how different types of brand measures relate to firm value remains under-researched. Finally, I analyze the heterogeneity in the effects of both brand measures in explaining firm value across types of goods to provide more nuanced managerial implications.

I combine data on real-time and survey-based brand measures for 46 brands from different industries with consumer mindset metrics data and abnormal stock returns over 130 weeks starting July 1, 2016. Granger causality tests (Granger 1969) show mutual temporal dependencies among the variables, highlighting the need for a dynamic investigation. Based on that, three vector autoregressive (VAR) models are estimated for each brand separately: one dual-brand metric model encompassing both brand measures and two single-brand metric models containing either the real-time or survey-based brand measure.

The contributions of this research to marketing theory and practice are as follows. In line with previous research emphasizing the difference between enduring attitudes and contextual online interest (Pauwels and van Ewijk 2020), the low and negative correlation between real-time and survey-based brand measures across brands and industries suggests that both brand measures capture different aspects of consumer brand perceptions, complementing each other.

This complementary effect is supported by the higher explanatory power of the model, which incorporates both brand measures, as opposed to the single-brand metric models. Additionally, the survey-based brand measure exhibits a slightly higher explanatory power than the real-time brand measure in the dual-brand metric model. Considering anecdotal evidence indicating that 80% of business leaders anticipate increasing their social media analytics budgets in the upcoming years (SproutSocial 2023), the findings of this research caution managers against devoting their budget solely to social media monitoring. This is especially true for service brands, for which the real-time brand measure is even less powerful in explaining firm value. Hence, this research not only extends previous findings on the complementary effects of online and survey-based metrics but also provides further guidance for managers on how to measure consumer brand perceptions, an ongoing marketing research priority (Marketing Science Institute 2018; Marketing Science Institute 2022).

2 Theoretical and Conceptual Background

Measuring consumer perception of brands is essential for both marketing literature and practice. While traditional brand measures are derived from directly asking consumers for their brand perceptions through large-scale surveys, more recent approaches exploit the rich brand-related data on social media. The following section provides a brief review of both methods.

2.1 Survey-Based and Real-Time Brand Measures

The most prominent survey-based brand measures recognized by marketing research are Young & Rubicam's Brand Asset Valuator (BAV), Harris Interactive's EquiTrend, and YouGov's BrandIndex (see Table 1). Young & Rubicam's BAV is available quarterly or annually and is based on a large sample of consumers, covering thousands of brands in 32 countries. Its four pillars – energized differentiation, relevance, esteem, and knowledge (Datta, Ailawadi, and van Heerde 2017; Mizik and Jacobson 2008) – align well with theoretical marketing concepts such as Keller's (1993) CBBE framework (Stahl et al. 2012). For example, both Keller (1993) and the BAV regard unique brand associations (covered by the energized differentiation pillar of the BAV) and brand knowledge as important components of consumer brand perceptions. Not surprisingly, the BAV is widely used in marketing literature and has been related to sales-based brand equity (Datta, Ailawadi, and van Heerde, 2017), unanticipated stock returns (Mizik and Jacobson 2008), customer acquisition, retention, profit margin (Stahl et al. 2012), and offline and online word-of-mouth (WOM; Lovett, Peres, and Shachar 2013). Similarly, the EquiTrend measure, which is only available annually, has previously been associated with stock performance (Aaker and Jacobson 1994; Johansson, Dimofte, and Mazvancheryl 2012) and idiosyncratic risk (Rego, Billett, and Morgan 2009).

More recently, the brand metrics by YouGov, a global market research company, are gaining attention. Its primary strength is the data's granularity; YouGov's brand metrics are available to paying clients on a daily basis. Each day, YouGov surveys thousands of consumers in 55 markets[22]. Three categories of data are offered: media and communication metrics (e.g., awareness), purchase funnel metrics (e.g., purchase intention), and brand perception metrics. The latter constitutes YouGov's focal brand measure, the BrandIndex, a multidimensional construct comprising the dimensions impression, quality, value, satisfaction, reputation, and recommendation. The overall BrandIndex is calculated as the average of the six dimensions and ranges from -100 to +100 (see Appendix A for details). While the impression and satisfaction dimensions cover consumers' general feelings toward the brand, the quality and value dimensions address consumers' perceptions of specific attributes. Finally, the reputation and recommendation dimensions capture specific behavioral intentions that extend beyond what consumers think and feel (see Table 2 for the exact questions).

[22] In the following, information regarding YouGov's measures are obtained either through internal conversations with the data provider or the user guide (YouGov 2022) given by the data provider.

Table 1: Comparison of Existing Brand Measures

Measure	Granularity	Dimensions	Conceptual relationship	Data source	Relevant marketing literature
Brand reputation tracker	Weekly, monthly, quarterly	Three drivers: value, brand, and relationship with sub-drivers	Rust et al. (2000) customer equity framework	X (formerly Twitter) posts from current and prospective customers, employees, shareholders	Rust et al. (2021)
YouGov's BrandIndex	Daily, annually	Six metrics: impression, quality, value, satisfaction, recommendation, and reputation	Aaker's (1996) Brand Equity Ten	Consumer perception surveys	Colicev et al. (2018); Kübler, Colicev, and Pauwels (2020); Luo, Raithel, and Wiles (2013); Stäbler and Fischer (2020)
Young & Rubicam's Brand Asset Valuator (BAV)	Quarterly, annually	Four pillars: energized differentiation, relevance, esteem, and knowledge	Keller's (1993) CBBE framework	Consumer perception surveys	Datta, Ailawadi, and van Heerde (2018); Lovett, Peres, and Shachar (2013); Mizik and Jacobson (2008); Stahl et al. (2013)
Harris Interactive's EquiTrend	Annually	Three key factors: familiarity, quality, and purchase consideration	Aaker's (1996) Brand Equity Ten	Consumer perception surveys	Aaker and Jacobson (1994); Rego, Billett, and Morgan (2009); Johansson, Dimofte, and Mazvancheryl (2012)

The dimensions quality, value, and satisfaction map well to the perceived value, perceived quality, and satisfaction/loyalty dimensions of Aaker's (1996) Brand Equity Ten. In addition, Aaker (1996) considers consumer associations with the firm behind the brand as an important aspect of brand measures. This view is partly reflected in the reputation dimension of YouGov's BrandIndex, which captures consumers' evaluations of the company behind the brand as a possible employer. Previous research has already applied the BrandIndex measure to investigate the impact of brand perceptions on firm value (Colicev et al. 2018; Luo, Raithel, and Wiles 2013).

In contrast to survey-based brand measures, real-time measures enable tracking brand perceptions at a more dynamic and granular level, i.e., intra-daily. In this respect, social media is increasingly gaining importance as a platform where consumers discuss brands extensively (Fossen and Schweidel 2019; Hewett et al. 2016). Although previous research has already used user-generated content (UGC) on social media to measure consumer brand sentiment (e.g., Colicev et al. 2018; Hewett et al. 2016; Kübler, Colicev, and Pauwels 2020), to the best of my knowledge, only Rust et al. (2021) have developed a readily available and theory-based real-time brand measure. This brand measure, called the brand reputation tracker, builds on X (formerly Twitter) data for 100 global brands that are ranked among the top 100 most valuable brands by various popular industry rankings (e.g., Interbrand). To compile the brand reputation tracker, the authors first identified the usernames for all 100 brands and collected all tweets directed at or from that username (e.g., @Nike). Based on the customer equity framework (Rust, Zeithaml, and Lemon 2000; Rust, Lemon, and Zeithaml 2004), three main drivers (value, brand, and relationship) and 11 sub-drivers were established (see Table 2; Rust et al. 2021). The authors then generated a list of keywords to create positive and negative dictionaries for each sub-driver. Based on the developed dictionaries, they counted the number of positive and negative tweets for each sub-driver and brand in a given period, such as a week (Rust et al.

2021). This methodology follows a top-down text analysis approach (Humphreys and Wang 2018). The net score for each sub-driver is calculated by subtracting the number of negative tweets from the number of positive tweets and standardizing the values across brands. The average of the respective sub-drivers constitutes the three main drivers, and the average of these three main drivers forms the overall brand reputation (see Rust et al. 2021 for details). So far, brand reputation and its drivers have been linked to brand buzz, consumers' purchase intention, and the brand's stock market performance, validating the measure and emphasizing its financial accountability (Rust et al. 2021).

2.2 Comparison of Survey-Based and Real-Time Brand Measures

As YouGov's BrandIndex is available at a more granular level than other survey-based brand measures, it is considered the primary survey-based brand measure in this research. In the following, brand reputation is compared theoretically to YouGov's BrandIndex. First, both measures capture what consumers feel and think about a brand. While YouGov's BrandIndex mainly focuses on consumer perceptions, the brand reputation tracker considers a broader range of stakeholders (e.g., investors or employees). In addition, brand reputation tracks actual consumer behavior in the form of what consumers talk about a brand. YouGov's BrandIndex, on the other hand, can at most capture behavioral intentions, such as intentions to recommend the brand to others (Rust et al. 2021; YouGov 2022).

Table 2 compares the sub-drivers of brand reputation to the dimensions of YouGov's BrandIndex. The first driver of brand reputation is value, which consists of the price, service quality, and goods quality sub-drivers. Conceptually, these sub-drivers of brand reputation map well on the value and quality dimensions of YouGov's BrandIndex measure. Perceived value and quality are also important dimensions in Aaker's (1996) Brand Equity Ten. The second driver brand, consisting of the sub-drivers cool, exciting, innovative, and social responsibility, represents the consumers' overall positive or negative perception of the brand. This aligns partly with the impression dimension of BrandIndex, which also captures consumers' overall positive or negative feelings toward the brand. Finally, brand reputation encompasses a relationship driver that includes aspects such as the personal relationship between the brand and its stakeholders (Rust et al. 2021). This driver does not match any of the BrandIndex dimensions. Similarly, the BrandIndex dimensions reputation, recommendation, and satisfaction are not captured by the brand reputation drivers. Thus, in these aspects, both brand measures complement each other conceptually.

Additionally, both brand measures exhibit complementary methodological advantages and disadvantages. Survey-based measures, including YouGov's BrandIndex measure, are time-consuming and costly to collect and suffer from common survey biases such as social desirability bias (Fisher 1993; Pauwels and van Ewijk 2020). Real-time brand measures are less costly due to the high availability of data on social media, are not noticeable to consumers while being collected, and thus are less susceptible to common surveying issues (Dzyabura and Peres 2021; Pauwels and van Ewijk 2020). In contrast, real-time brand measures that are based on social media might not cover all target customers (e.g., older consumers), are harder to obtain for unpopular product categories (e.g., food) or brands, and are potentially biased by polarized opinions, manipulations (e.g., bots), or social signaling (Dzyabura and Peres 2021; Lovett, Peres, and Shachar 2013; Pauwels and van Ewijk 2020; Read 2018; Schoenmueller, Netzer, and Stahl 2023). These weaknesses are mitigated by survey-based measures that cover a wider range of products and markets (most providers of survey-based measures also weigh the answers to ensure representativeness), are standardized across product categories, and cannot be easily manipulated (Dzyabura and Peres 2021; YouGov 2022).

Table 2: Comparison of the Sub-Drivers/Dimensions of Brand Measures

Brand reputation drivers	Brand reputation sub-drivers	Questions [a]	YouGov dimensions	Questions [b]
Value	**Price**	Is the brand known for low prices, such as being cheap, affordable, having deals, bargains, discounts, and sales?	**Value**	Which of the following brands do you think represents good/poor value for money?
	Service quality	Does the brand provide high quality service, such as being competent, helpful, fast, knowledgeable, understanding, with patient and respect?	**Quality**	Which of the following brands do you think represents good/poor quality?
	Goods quality	Does the brand create high quality products, such as durable, functional, strong, beautiful, and valuable?		
Brand	**Cool**	Is the brand known for being trendy, hip, awesome, cool, stylish, and sexy?	**Impression**	Which of the following brands do you have a generally positive/negative feeling about?
	Exciting	Does the brand bring a sense of excitement to its products/ services, such as being fun, exciting, inspiring, and stimulating?		
	Innovative	Is the brand new, smart, technologically advanced, intelligent, innovative, creative, novel, and cutting edged?		
	Social responsibility	Is the brand caring, benevolent, giving and beneficial?		
Relationship	**Community**	Does the brand generate a sense of community, such that people are involved, together, and harmonious with the brand, and can communicate and be social with the brand?		
	Friendly	Is the brand nice, pleasant, warm, kind, open, and accommodating?		
	Personal relationships	Does the brand connect personally with its stakeholders by being special, personal, intimate, and close?		
	Trustworthy	Is the brand honest, reliable, dependable?		
			Reputation	Imagine you were looking for a job (or advising a friend looking for a job). Which of the following companies would you be proud/embarrassed to work for?
			Recommendation	Which of the following brands would you recommend/tell a friend to avoid?
			Satisfaction	Which of the following brands would you say that you are a satisfied/dissatisfied customer of?

Notes: [a] The drivers, sub-drivers and questions of brand reputation are obtained from Rust et al. (2021). [b] The specific questions of the YouGov BrandIndex dimensions come from a user guide provided by YouGov and are from June 2023 (YouGov 2022).

2.3 Complementary Effects of Survey-Based and Online Metrics

Prior research has well-documented the added value of either online or survey-based metrics in explaining and predicting sales above the effect of marketing actions (e.g., Srinivasan, Rutz, and Pauwels 2016; Srinivasan, Vanhuele, and Pauwels 2010). Recent work has extended this view by integrating online and survey-based metrics into one framework, relating them, and comparing their explanatory power on sales and firm value (Colicev et al. 2018; de Vries, Gensler, and Leeflang 2017; Hewett et al. 2016; Kübler, Colicev, and Pauwels 2020; Pauwels and van Ewijk 2020). They either posit online consumer sentiment about brands as a pre-stage of survey-based mindset metrics such as brand awareness or purchase intention (Colicev et al. 2018; de Vries, Gensler, and Leeflang 2017; Kübler, Colicev, and Pauwels 2020) or compare survey-based mindset metrics to online consumer behavior such as website visits (Pauwels and van Ewijk 2020). Table 3 summarizes the relevant prior literature and presents the extension of the current work.

For instance, Colicev et al. (2018) highlight how social media metrics add to firm value through survey-based consumer mindset metrics (i.e., brand awareness, purchase intention, and customer satisfaction). They differentiate between firm-owned and earned social media content, showing that both factors impact survey-based mindset metrics. De Vries, Gensler, and Leeflang (2017) demonstrate similar effects on customer acquisition. Kübler, Colicev, and Pauwels (2020) extend previous work by comparing the strength of different online metrics in explaining survey-based consumer mindset metrics. They compare volume metrics (e.g., number of likes or comments) with valence metrics based on different sentiment extraction tools, from dictionary-based to machine learning approaches. Their findings posit that no single metric always performs the best. The choice of metric depends on the consumer mindset metric (e.g., volume metrics work best for brand awareness and purchase intentions, while machine learning approaches perform better for brand impression, satisfaction, and recommendation), the brand strength, and the type of good (search versus experience goods). However, combining different metrics is superior. Pauwels and van Ewijk (2020) support this notion by demonstrating that online behavior metrics (e.g., website visits) and survey-based consumer mindset metrics both contribute to explaining sales. The former performs better in same-week sales explanations in high-involvement categories, while the latter excels in sales prediction in low-involvement categories.

Table 3: Extension to Prior Literature

Paper	Marketing metrics	Survey-based metrics	Online metrics	Performance metrics	Comparison of brand measures
Colicev et al. 2018	–	Brand awareness, Satisfaction, Purchase intent	Earned social media volume, positive valence, negative valence, brand fan following, Owned social media	Abnormal stock returns, Idiosyncratic risk	–
Kübler, Colicev, and Pauwels 2020	–	Awareness, Impression, Purchase intent, Satisfaction, Recommendation	Likes volume, Shares volume, Comments volume, Comments sentiment	–	Comparison of different social media-based brand measures but no comparison to survey-based brand measures
Pauwels, Aksehirli, and Lackman 2016	TV, Radio, Print	–	Organic search, Paid search, Brand eWOM, Ad eWOM, Purchase eWOM	Store traffic, Online traffic	
Pauwels and van Ewijk 2020	Advertising, Price, Promotion	Awareness, Consideration, Preference	Branded search, Generic search, Website visits, Page views	Sales	–
Srinivasan, Rutz, and Pauwels 2016	Advertising, Price, Distribution	–	Website visits, Search clicks, Facebook likes/dislikes	Sales	–
This study	**–**	**BrandIndex, Brand awareness, Brand purchase**	**Brand reputation**	**Abnormal stock returns**	**Comparison of real-time and survey-based brand measures**

Notes: eWOM = electronic word of mouth.

This research contributes to the existing literature by directly comparing two equivalent yet methodologically distinct brand measures, i.e., real-time brand measures and survey-based brand measures. Compared to Pauwels and van Ewijk (2020), the current research does not compare online *behavior* metrics to survey-based *attitude* metrics but contrasts *two attitudinal brand measures*. Contrary to Kübler, Colicev, and Pauwels (2020), one of these brand measures is survey-based. Thus, this research addresses the still inconclusive question of how to measure consumer brand perceptions best and whether and how real-time brand measures can complement or even substitute survey-based brand measures. Based on previous literature findings, I expect that real-time and survey-based brand measures complement each other in explaining firm value.

2.4 Heterogeneity in the Complementary Effect of Brand Measures

Following the proposition that real-time brand measures should complement survey-based brand measures in explaining firm value, the question arises when this complementary effect is especially pronounced. The main argument is that the complementary effect increases with the value of the real-time brand measure. Whereas survey-based brand measures are standardized across brands, the effectiveness of real-time brand measures may vary for two main reasons. First, consumers can self-determine what to talk about online. Thus, information on consumer perceptions regarding certain categories, products, or brands may be restricted (Dzyabura and Peres 2021; Lovett, Peres, and Shachar 2013). For example, online brand mentions in categories such as media and entertainment, technology, or cars greatly exceed mentions in categories like health or beverages (Lovett, Peres, and Shachar 2013). Second, a top-down text analysis approach as used for the brand reputation tracker might not adequately capture consumer perceptions for all brands and categories. Previous research has demonstrated that the effectiveness of different types of sentiment extraction tools might differ depending on the type of goods, i.e., search versus experience goods (Kübler, Colicev, and Pauwels 2020). I follow this work and argue that the added value of real-time brand measures, such as the brand reputation tracker, depends on the type of good (i.e., whether the brand offers a service or a manufacturing good).[23]

The quality and performance of service goods can only be fully evaluated after experiencing them (i.e., experience goods; Nelson 1970). However, the language used to express experiences is highly variable, complex, and sometimes ambiguous. For example, the following tweet, although containing more positive words, describes a negative experience: "@Delta Losing my bag is a great way to keep me as a customer" (Kübler, Colicev, and Pauwels 2020, p. 141). While a top-down dictionary-based text analysis approach would falsely classify this tweet as positive due to the higher number of positive words, more sophisticated machine learning approaches might better recognize the true negative character of the tweet (Humphreys and Wang 2018; Kübler, Colicev, and Pauwels 2020). In contrast, manufacturing goods are more clearly defined based on technical aspects that are easier to classify as positive or negative. In this case, using top-down dictionary-based text analysis tools to extract consumer brand perceptions might be sufficient (Humphreys and Wang 2018). Thus, I expect the complementary effect of both brand measures to be higher for manufacturing brands than service brands.

3 Data

3.1 Real-Time Brand Measure

The final dataset combines data from five sources (see Table 4). Real-time brand data is based on the brand reputation tracker by Rust et al. (2021). The authors provide publicly available weekly, monthly, and quarterly data on the value, brand, and relationship sub-drivers for 100 global brands[24]. Brand reputation is then calculated as the average of the three sub-

[23] I divide type of goods into manufacturing or service instead of search versus experience as proposed by Kübler, Colicev, and Pauwels (2020) because the categorization of brands into manufacturing or service is more straightforward than the categorization into search versus experience.
[24] Data on the brand reputation tracker is available at https://osf.io/6nzrk/.

drivers. As the data on brand reputation is provided on a weekly basis at the lowest frequency, I aggregate all data on a weekly level.[25]

Table 4: Variable Description and Operationalization

Variables	Type	Description	Source
Abnormal returns	Dependent/ Explanatory	Abnormal stock returns calculated using the Fama and French (1993) and Carhart (1997) four-factor model.	Beta Suite by WRDS
Brand reputation	Explanatory	The overall impression of how stakeholders think, feel, and talk about a brand as the average of the drivers value, brand, and relationship.	Rust et al. (2021); https://osf.io/6nzrk/
BrandIndex	Explanatory	Multidimensional index that reflects consumers' perceptions of the brand and is calculated as the average of the six dimensions impression, quality, value, satisfaction, reputation, and recommendation.	YouGov
Brand awareness	Explanatory	Brand awareness consists of aided awareness and ad awareness.	YouGov
Brand purchase	Explanatory	Brand purchase consists of consideration, purchase intent, and whether the respondent is a current customer.	YouGov
Dividend announcements	Control	Announcements of dividend distributions to shareholders.	CRSP
M&A announcements	Control	Announcements of mergers and/or acquisitions of other companies.	Lexis Nexis
Quarterly dummies	Control	Quarterly dummies for each quarter with the first quarter as the baseline.	–
Time trend	Control	Continuous variable capturing the time trend with the first week as the baseline.	–

3.2 Survey-Based Brand Measure and Mindset Metrics

Survey-based brand data and other consumer mindset metrics are obtained from YouGov, a market research company that utilizes online consumer panels to monitor brands daily. YouGov metrics have been used in previous marketing research studies across various settings

[25] In a private conversation, the authors of Rust et al. (2021) indicated that for the brand reputation tracker a week is defined from Friday to Thursday.

(e.g., Colicev et al. 2018; Luo, Raithel, and Wiles 2013; Stäbler and Fischer 2020). In the U.S. market, YouGov monitors over 1,900 brands by surveying 5,500 consumers daily[26]. For representativeness reasons, the sample is weighted by demographics such as age, gender, and region. Generally, YouGov monitors three broad sets of metrics: media and communications metrics, purchase funnel metrics, and brand perception metrics. The first two sets of metrics capture what brands consumers hear about, talk about, and use. Brand perception metrics, consisting of impression, quality, value, satisfaction, reputation, and recommendation, are averaged to form YouGov's BrandIndex, ranging from -100 to +100.

I use the BrandIndex measure as the survey-based brand measure and combine it with media and communications and purchase funnel metrics to form the consumer mindset metrics and recreate the stages of the consumer decision journey (Colicev et al. 2018). Following past research (Colicev et al. 2018; Valenti et al. 2023), I operationalize the consumer mindset metric brand awareness as the average of the YouGov metrics aided awareness and advertising awareness, and the consumer mindset metric brand purchase as the average of the YouGov metrics consideration, purchase intent, and current customer. To validate the relationship of the combined metrics, I perform a factor analysis with varimax rotation across brands. The results support a two-factor solution with all factor eigenvalues higher than 1. Each metric loads higher on one of the factors than the other factor, indicating good discriminant validity (see Appendix A for details). All data are downloaded on a daily level and then aggregated to weekly data in alignment with the brand reputation data.

3.3 Firm Value

Firm value is captured by abnormal stock returns obtained from WRDS Beta Suite, a tool that allows researchers to calculate abnormal stock returns and risk factors with different

[26] As the final dataset contains mostly U.S.-based brands (83%), I use YouGov metrics obtained from the U.S. market. The number of brands and consumers surveyed are from June 2023.

models (e.g., CAPM or Fama-French) on a monthly, weekly, or daily rolling regression basis (for recent applications in the marketing literature see McCarthy and Winer 2019; Morgeson et al. 2023). I calculate the abnormal returns using the Carhart four-factor model, which expands the original Fama-French three-factor model by a momentum factor (Carhart 1997; Fama and French 1993), as specified in Equation 1:

$$(R_{id} - R_{fd}) = \alpha_i + \beta_{1i}(R_{md} - R_{fd}) + \beta_{2i}SMB_d + \beta_{3i}HML_d + \beta_{4i}UMD_d + \varepsilon_{id} \tag{1}$$

where R_{id} is the actual stock return of brand *i* in day *d*, and R_{fd} is the risk-free rate of return, R_{md} is the average market return, SMB_d is the size factor, HML_d is the value factor, UMD_d is the momentum factor, α_i is the intercept, β_i are the coefficients to be estimated, and ε_{id} is the model residual. The daily abnormal stock returns AR_{id} are calculated as the difference between actual stock returns and the expected stock returns using the following formula, where $\hat{\alpha}$ and $\hat{\beta}$ are the estimated coefficients:

$$\begin{aligned} AR_{id} = (R_{id} - R_{fd}) - [\hat{\alpha}_i + \hat{\beta}_{1i}(R_{md} - R_{fd}) + \hat{\beta}_{2i}SMB_d + \hat{\beta}_{3i}HML_d \\ + \hat{\beta}_{4i}UMD_d]. \end{aligned} \tag{2}$$

This procedure is replicated for every brand with a rolling window of 250 days (Colicev et al. 2018). I aggregate the daily abnormal stock returns for brand *i* to obtain the weekly returns using the compounding formula: $AR_{it} = \prod[(1 + AR_{id})] - 1$, where AR_{it} represents the abnormal stock returns of brand *i* in week *t*.[27]

3.4 Control Variables

Following previous research (Colicev et al. 2018), I include the following control variables in the model: dividend distribution announcements from CRSP, merger and acquisition (M&A) announcements manually researched in the LexisNexis database, quarterly dummies to account

[27] To better align the weekly brand reputation data with the abnormal returns data from WRDS Beta Suite, I use daily abnormal returns and aggregate it on a weekly basis from Friday to Thursday.

for seasonal fluctuations and a deterministic trend to capture the impact of omitted, gradually changing variables.

3.5 Final Sample

I successfully obtained a balanced dataset comprising 46 brands from 6 industries (see Table 5) spanning over 130 weeks from July 1, 2016, to December 27, 2018. The observation period and set of brands are based on the availability of the brand reputation data for 67 single (corporate) brands listed on the stock market (Rust et al. 2021). I follow past research and only consider firms with a corporate branding strategy (e.g., Colicev et al. 2018; Rust et al. 2021) as it facilitates the attribution of the brand to the firm's stock performance. Out of the 67 listed single brands, only 46 brands are covered by YouGov over the observation period, further limiting the brands included in the final dataset.

Table 5: Sample of Brands

Industry classification	Brands	Type of goods
Accommodation and food services	McDonald's, Starbucks	Service
Financial/professional and scientific services	American Express, Bank of America, HSBC, IBM, MasterCard, Wells Fargo	Service
Information	AT&T, CBS Corporation, Facebook, Fox Broadcasting Company, Google, Microsoft, Twitter, Visa	Service
Manufacturing	Apple, Canon, ExxonMobil, General Electric, General Mills, Hewlett-Packard, Honda, Intel, John Deere, Nike, Nokia, Philips, Revlon, Shell, Sony, Toyota	Manufacturing
Transportation and warehousing	American Airlines	Service
Wholesale/Retail	Amazon, Barnes & Noble, Coach, Costco, eBay, Macy's, Nordstrom, Ralph Lauren, Sunoco, Target, The Home Depot, Walgreens, Walmart	Service

Notes: Following Rust et al. (2021), the industry classification is based on the two-digit NAICS classification system at the beginning of the observation period. Only listed single brands that are covered by YouGov over the whole observation period are included.

4 Methodology

4.1 Model Selection

The economic model selection in this study is driven by two main factors of the research context. First, previous research highlights mixed findings regarding the temporal sequence of effects among consumer mindset metrics (e.g., Srinivasan, Vanhuele, and Pauwels 2010; Vakratsas and Ambler 1999; Valenti et al. 2023). For example, a more positive brand perception may lead to higher brand awareness and ultimately higher purchase intentions, which subsequently can affect brand perceptions again. Likewise, the chain of effects can start with brand awareness, so that consumers talk more about brands they are more familiar with. Furthermore, media coverage of unexpected changes in stock prices, such as the GameStop short squeeze example (Davies 2021), can increase brand awareness and impact brand perceptions. Second, due to these feedback effects, the full performance implications of these variables may only be realized in later periods (Srinivasan, Vanhuele, and Pauwels 2010). To capture these dynamic and feedback effects, I adopt the persistence-modeling framework (Dekimpe and Hanssens 1995) and apply the vector autoregressive (VAR) modeling approach (see also Colicev et al. 2018; Kübler, Colicev, and Pauwels 2020; Pauwels and van Ewijk 2020; Srinivasan, Vanhuele, and Pauwels 2010). The key advantage of VAR models is that all endogenous variables are estimated simultaneously without imposing a causal ordering (Leeflang et al. 2017). Therefore, VAR models account for potential endogeneity between the brand measures, the consumer mindset metrics, and firm value. Specifically, I use VARX models, which extend the simple VAR models by controlling for the effects of exogenous variables.

4.2 *Model Specification*

The specification of the VARX models follows a set of different methodological steps adapted from previous literature (e.g., Pauwels and van Ewijk 2020; Srinivasan, Vanhuele, and Pauwels 2010; see Table 6). First, using a two-step process, I assess the univariate properties of each explanatory variable's time series through unit root tests for each brand separately. In the first step, I apply augmented Dickey-Fuller unit root tests, following the iterative process proposed by Enders (2004).[28] In the next step, I visually inspect all explanatory variables' time series to check the presence of structural breaks and, if applicable, apply the Zivot and Andrews (1992) unit root test for structural breaks to avoid falsely assuming the presence of a unit root. If structural breaks are present, an additional control variable is included in the VARX models (Valenti et al. 2023).

In the second step, I verify the need for a dynamic modeling approach through Granger causality tests for each pair of the explanatory variables (Granger 1969). If a variable Y is Granger caused by another variable X, then Y can be better predicted if past values of X are known in addition to past values of Y. I apply the Dumitrescu and Hurlin (2012) panel causality test to account for brand-level heterogeneity. Following past research, I test for lags from 1 to 13 (i.e., one quarter) and report the results for the lag with the lowest p-value in the Granger causality tests (Pauwels and van Ewijk 2020; Trusov, Bucklin, and Pauwels 2009).

Third, the optimal lag for each VARX model is selected according to the Akaike information criterion (AIC) and accounting for autocorrelation using the Breusch-Godfrey LM test for serial correlation (Breusch 1978; Godfrey 1978). If the model with the proposed optimal lag length by AIC displays serial correlation, I test additional models up to five lags and add lags until no serial correlation is present (Colicev et al. 2018; Franses 2005). If the model's

[28] To avoid falsely not rejecting the null hypothesis of a unit root, Enders (2004, pp. 181-183) proposes an iterative process to decide whether to include a deterministic trend and drift, only a drift, or no trend and no drift in the unit root tests in case the actual data-generating process is unknown.

serial correlation does not improve when adding up to five lags, I use the lag length proposed by AIC for parsimony. [29] More details on the VARX model specification are provided in Appendix C.

Table 6: Overview of the Methodological Steps

	Methodological steps	Research question addressed	Literature
1	Unit root test	Are variables stationary or evolving based on Augmented Dickey-Fuller unit root tests?	Enders (2004)
	Structural break	Is there a structural break in the time series?	Zivot and Andrews (1992)
2	Granger causality test	What is the temporal order among variables?	Granger (1969)
3	Lag selection criteria	What is the optimal lag based on the Akaike information criterion (AIC)?	Pauwels and van Ewijk (2020)
	Serial correlation	Does the number of lags have to be increased to account for serial correlation based on Breusch-Godfrey LM serial correlation tests?	Colicev et al. (2018)
4	Vector autoregressive (VARX) models	How do the endogenous variables interact accounting for exogenous factors?	Dekimpe and Hanssens (1995)
5	Generalized forecast error variance decomposition (GFEVD)	What is the explanatory power of each model? What is the relative importance of each variable in explaining the variance in firm value?	Pesaran and Shin (1998)

Notes: Methodological steps are adapted from previous literature (e.g., Pauwels and van Ewijk 2020; Srinivasan, Vanhuele, and Pauwels 2010).

In the fourth step, I estimate the VARX models as specified based on the results of the unit root tests, the Granger causality tests, and the optimal lag selection. For the model including both brand measures, I specify the VARX model as follows:

[29] To keep the observation-to-parameter ratio (see Appendix C) around the proposed level of 5 (Leeflang et al. 2015), I only test models up to five lags and add lags if the model's serial correlation can be improved up to five lags.

$$\begin{bmatrix} Brand\ reputation_t \\ BrandIndex_t \\ Brand\ awareness_t \\ Brand\ purchase_t \\ Abnormal\ returns_t \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{bmatrix} + \sum_{n=1}^{p} \begin{bmatrix} \gamma_{1,1}^n & \cdots & \gamma_{1,5}^n \\ \vdots & \ddots & \vdots \\ \gamma_{5,1}^n & \cdots & \gamma_{5,5}^n \end{bmatrix} \begin{bmatrix} Brand\ reputation_{t-n} \\ BrandIndex_{t-n} \\ Brand\ awareness_{t-n} \\ Brand\ purchase_{t-n} \\ Abnormal\ returns_{t-n} \end{bmatrix} + \begin{bmatrix} \varphi_{1,1} & \cdots & \varphi_{1,7} \\ \vdots & \ddots & \vdots \\ \varphi_{5,1} & \cdots & \varphi_{5,7} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \\ e_{4,t} \\ e_{5,t} \end{bmatrix}, \tag{3}$$

where **A** is a vector of intercepts, brand reputation, BrandIndex, brand awareness, brand purchase and abnormal returns are the endogenous variables as verified by the Granger causality test results, p is the optimal number of lags based on AIC and serial correlation tests, and **X** is a vector of exogenous control variables, including a deterministic trend to account for the impact of omitted, gradually changing variables, quarterly dummies to capture seasonality, two count variables, one for M&A announcements and one for dividend distribution announcements, and, if applicable, a dummy variable accounting for structural breaks in the time series. The vector of errors $\boldsymbol{\varepsilon}$ contains the residual variance-covariance matrix, which captures the contemporaneous effects of the endogenous variables. In total, I estimate three models for each brand separately: a dual-brand metric model containing both real-time and survey-based brand measures and two single-brand metrics models, which either contain the real-time brand measure (i.e., brand reputation) or the survey-based brand measure (i.e., BrandIndex). The single-brand metrics models are specified analogously to the dual-brand metric model in Equation 3, ommitting either BrandIndex or brand reputation.

4.3 GFEVD Estimation

Estimating the three VARX models for each brand separately constitutes only the first step in answering the research questions of the current study. To assess the overall explanatory power of each model and the relative importance of each brand measure in explaining firm value, I derive the estimates for the generalized forecast error variance decomposition (GFEVD) from the VARX parameters of each model and brand. Similar to a "dynamic R^2", GFEVDs quantify the relative impact over time of shocks initiated by each endogenous variable in a VARX model, without imposing a causal ordering among them (Pesaran and Shin 1998; Srinivasan, Vanhuele, and Pauwels 2010). GFEVDs represent the central metric of this research as they provide a means to compare the explanatory power of different models and brand measures and have been used in previous research for similar purposes (e.g., Kübler, Colicev, and Pauwels 2020; Srinivasan, Vanhuele, and Pauwels 2010). Specifically, GFEVDs attribute the forecast error variance in an endogenous variable either to past values of itself or to past values of the other endogenous variables and thus sum up to 100% (Srinivasan, Vanhuele, and Pauwels 2010). I assess the explanatory power of each model and brand measure by the extent to which they explain the forecast error variance of firm value beyond the percentage explained by past abnormal stock returns. To reduce the sensitivity to short-term fluctuations and increase the comparability across brands, I follow previous research and evaluate GFEVDs at 10 weeks and only for brands with stationary endogenous variables (Pauwels and van Ewijk 2020; Srinivasan, Vanhuele, and Pauwels 2010).[30] Finally, I compare differences in GFEVDs between models and brand measures across types of goods (service versus manufacturing) to investigate brand-level heterogeneity.

[30] If variables are non-stationary, they enter the VARX model in differences so that they represent growth rates rather than levels (Leeflang et al. 2017; Srinivasan, Vanhuele, and Pauwels 2010). Restricting the analysis to brands with stationary variables only thus avoids comparing growth-rate variables to level variables, yielding more meaningful GFEVD comparisons across brands.

5 Results

5.1 Model-Free Analyses

The first empirical step shows model-free evidence in the form of correlations and graphical inspections of both brand measures and the other endogenous variables. This lays the foundation for the model-based comparison, in which the explanatory power of both brand measures combined and in separate models is analyzed.

5.1.1 Correlations

Table 7 presents the correlations among the endogenous variables averaged across the full set of brands (46 brands). The correlations between brand reputation and mindset metrics are low, confirming previous findings (e.g., Kübler, Colicev, and Pauwels 2020). While brand reputation is positively correlated with brand awareness (0.001), it is negatively associated with brand purchase (-0.028) and abnormal returns (-0.032). In contrast, BrandIndex exhibits a positive (weak to moderate) correlation with the other variables, with the strongest correlation being between BrandIndex and brand purchase (0.500).

Table 7: Correlations Between Variables (Averaged Across 46 Brands)

	Brand reputation	BrandIndex	Brand awareness	Brand purchase	Abnormal returns
Brand reputation	1.000				
BrandIndex	-0.035	1.000			
Brand awareness	0.001	0.082	1.000		
Brand purchase	-0.028	0.500	0.209	1.000	
Abnormal returns	-0.032	0.000	-0.002	0.001	1.000

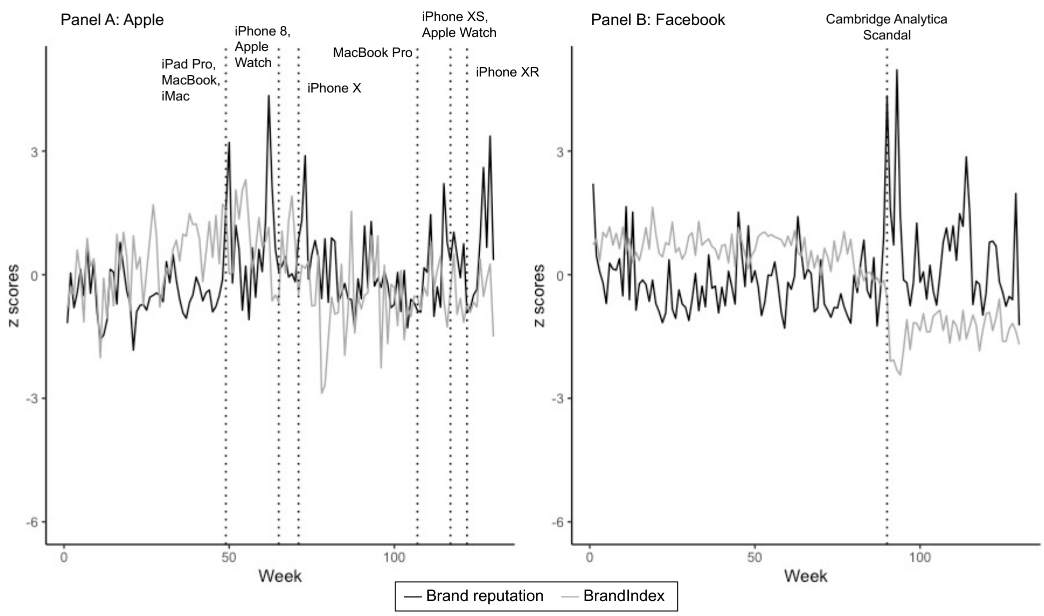
Interestingly, the correlation between the brand measures brand reputation and BrandIndex is weak and negative (-0.035). Although surprising, this finding is in line with prior research indicating a low correlation between online and offline metrics. First, Pauwels and van Ewijk (2020) show a low correlation between online behavior metrics and survey-based attitude metrics. Second, de Langhe, Fernbach, and Lichtenstein (2016) report a similarly low correlation between online user ratings and Consumer Reports scores, whereby 34% of the correlations are negative. Accordingly, I find a negative correlation between brand reputation and BrandIndex among 52% of the brands. Finally, Fay et al. (2019) report a lack of correlation between online and offline word-of-mouth metrics. The low and negative correlation among the brand measures suggests that they capture different aspects of consumer brand perceptions, supporting their complementary role.

5.1.2 Graphical inspections

In the next step, I graphically analyze how both brand measures react to controllable marketing events (e.g., product introductions) and uncontrollable external events (e.g., negative news) following Rust et al. (2021). For each event type, I select one brand example.

Apple serves as an example for controllable marketing events, as it holds on average three major product introduction events per year (MacRumors 2025). Figure 1 Panel A displays the standardized time series of brand reputation (in black) and BrandIndex (in grey) for Apple for 130 weeks starting July 1, 2016. Each dotted line represents a selected major product introduction event, such as the announcement of the latest iPhone, iPad, or MacBook (MacRumors 2017). While the time series for brand reputation shows high spikes before or after each major product announcement, the changes in BrandIndex are more subtle. In September each year, Apple typically introduces the latest iPhone, a highly anticipated event (MacRumors 2025). This anticipation of consumers is well-reflected in the behavior of the brand reputation time series, which shows a high and sudden spike before the event (see, for example, the introduction of the iPhone 8 in Figure 1 Panel A). In contrast, the BrandIndex time series does not exhibit a sudden spike but rather a slow increase in the mean over a longer period. These observations demonstrate that consumer reactions to brands online are faster and more extreme than offline attitude changes. Additionally, Figures A1-A2 in Appendix B display the relationships between the two brand measures and brand awareness, brand purchase, and abnormal returns. While BrandIndex behaves very closely to brand purchase, brand reputation relates closer to brand awareness.

Figure 1: Time Series of Brand Reputation and BrandIndex at Selected Events



Notes: The black line represents the standardized time series for brand reputation, while the grey lines represent the standardized time series for BrandIndex. The dotted lines represent the respective brand events.

Figure 1 Panel B displays the standardized time series of brand reputation (in black) and BrandIndex (in grey) for Facebook for 130 weeks starting July 1, 2016. This period captures one major uncontrollable external event, the Cambridge Analytica scandal on March 17, 2018, which revealed that Cambridge Analytica, a data analysis firm, had unauthorized access to Facebook user accounts (Cadwalladr and Graham Harrison 2018; see dotted line). As evident in Figure 1 and Figures A3-A4 in Appendix B, the negative news about Facebook caused a sharp decline in brand reputation, BrandIndex, brand purchase, and abnormal stock returns, while brand awareness increased. This shows that both brand measures adequately capture the negative external event. However, the difference is that the decrease in BrandIndex leads to a shift in mean, whereas brand reputation reverts back to approximately the pre-event value. This underlines the proposition in previous literature that survey-based attitudes are more enduring while online behavior (e.g., talking about brands online) represents contextual (and probably short-lived) interests (Pauwels and van Ewijk 2020) as reflected in the high but mean-reverting spikes in brand reputation.

Overall, both the low and negative correlation and the partly different reactions to brand events indicate that real-time and survey-based brand measures may capture different aspects of consumer perceptions, fulfilling complementary roles in explaining firm value. I analyze this proposition further in the following dynamic analyses.

5.2 VARX Model Specification and Fit

Based on the two-step process described before, unit root tests reveal that for most brands (~72%), all variables are stationary. Following Srinivasan, Vanhuele, and Pauwels (2010), I focus on those 33 brands (out of 46 brands) for comparability reasons and report the average results as averages across those 33 brands (see Appendix C for details).

The results of the Granger causality tests verify the dynamic relationship between the endogenous variables (see Table A4 in Appendix C). The VARX models contain up to five endogenous variables, which results in 20 possible pairwise combinations. Out of these 20 possible pairs of variables, 15 show significant Granger causality ($p < 0.05$), confirming the need for a multiple-equation system as in Equation 3.

To specify the number of lags, I balance optimal lag selection based on AIC with autocorrelation bias and increase the number of lags if serial correlation can be improved with a higher lag order (Colicev et al. 2018; Franses 2005). As a result, 23 brands remain at lag one, while for the other brands, I increase the number of lags to two or three, depending on the results of the Breusch-Godfrey LM test (Breusch 1978; Godfrey 1978). The observation-to-parameter ratio exceeds the proposed threshold of 5 for all models (Leeflang et al. 2015; see Table A5 in Appendix C).

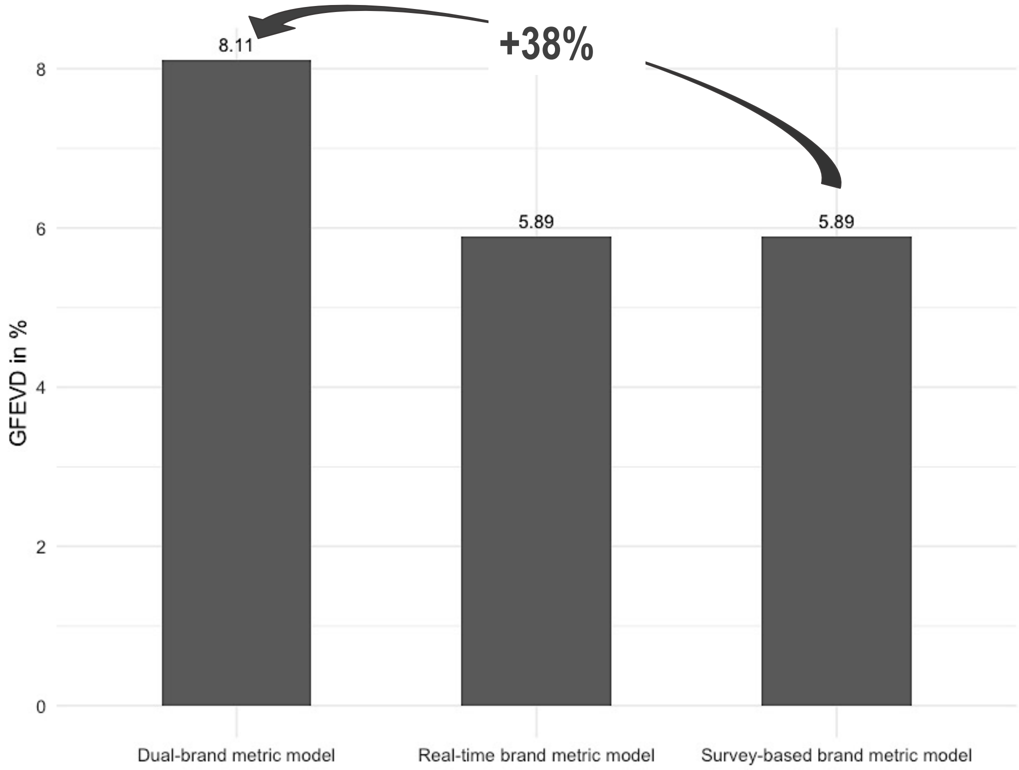
The VARX models display an acceptable average model fit for firm value. In the dual-brand metric model, model fit (R^2) is 0.116, while in the single-brand metric models, R^2 drops to 0.105 (survey-based brand metric model) and 0.099 (real-time brand metric model). Although low, these numbers are comparable to previous findings (e.g., Colicev et al. 2018) and imply that both brand measures play a role in explaining firm value. On the brand level, the dual-brand metric model outperforms the real-time brand metric model for 26 brands and the survey-based brand metric model for 29 brands. For the remaining brands, the dual-brand metric model performs equally to one of the single-brand metric models (see Table A6 in Appendix D).

5.3 Explanatory Power of Models and Brand Measures

Figure 2 displays the GFEVD results. In line with the previous findings, the GFEVD (dynamic R^2) results indicate that, on average, the dual-brand metric model outperforms both single-brand metric models in explaining firm value. Interestingly, the explanatory power of both single-brand metric models does not differ; the real-time brand metric model and the survey-based brand metric model explain 5.89% of the variance in firm value. In contrast, the dual-brand metric model shows the highest explanatory power (8.11%). Post-hoc tests using Bonferroni correction with repeated measures for companies reveal that the difference between the dual-brand and single-brand metric models is significant ($F(2, 64) = 25.21$, $p < 0.001$). Hence, combining both brand measures significantly improves the model's explanatory power by nearly 38%[31]. On the brand level, all 33 brands display an improvement in GFEVD for the dual-brand metric model compared to the single-brand metric models.

[31] Calculated as $\left[\frac{GFEVD_{dual-brand\ metric\ model} - GFEVD_{survey-based\ brand\ metric\ model}}{GFEVD_{survey-based\ brand\ metric\ model}}\right] \times 100$.

Figure 2: Explanatory Power (GFEVD) Across Models

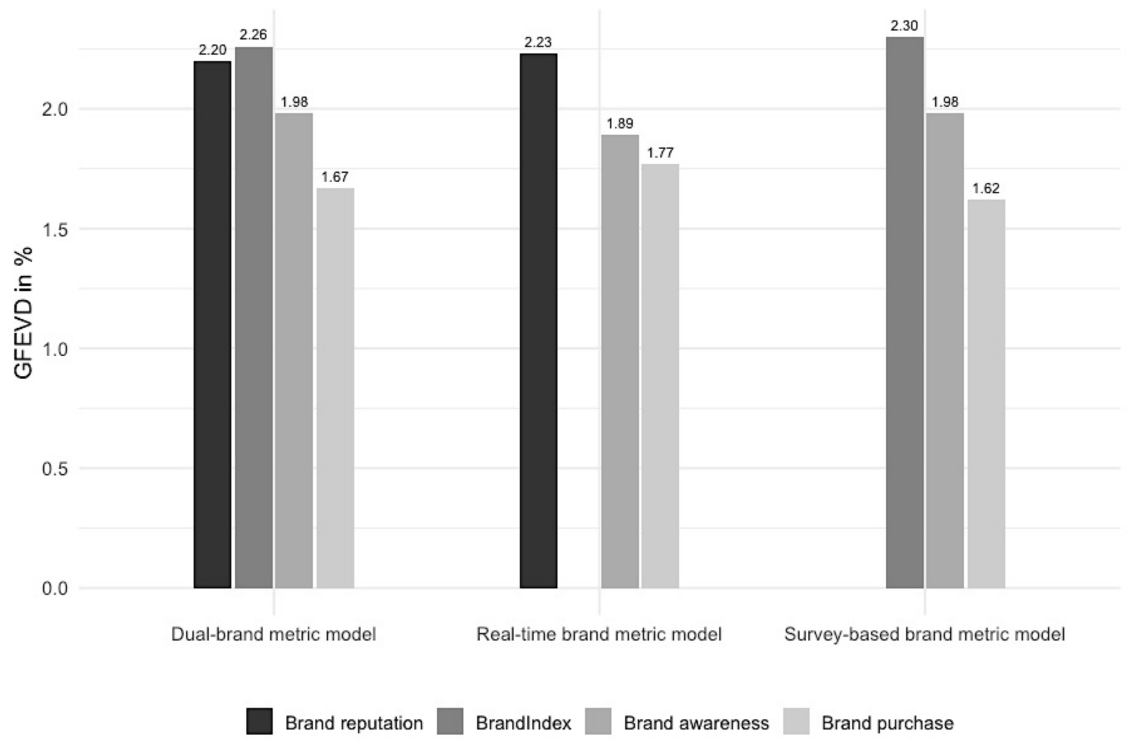


Notes: The total GFEVD of firm value for each model is summed across all endogenous variables except past abnormal stock returns and averaged across 33 brands. The remainder of the GFEVD can be attributed to past abnormal stock returns.

Figure 3 illustrates the extent to which the different variables drive the explanatory power of the models. When examining the average GFEVD for each variable in the dual-brand metric model, results show that BrandIndex accounts for most of the variation explained in firm value (2.26%), followed by brand reputation, which accounts for 2.20%. To compare, brand awareness and brand purchase account for only 1.98% and 1.67% of the variation in firm value (Figure 3). The same pattern can also be observed for the single-brand metric models, where the explanatory power of the brand measures on the variation in firm value is higher than that of the mindset metrics. Although the individual explanatory power of the brand measures increases in the single-brand metric models compared to the dual-brand metric model (e.g., the explanatory power of brand reputation rises from 2.20% in the dual-brand metric model to

2.23% in the real-time brand metric model), this increase is not statistically significant. This suggests that each brand measure individually cannot compensate much for the other.

Figure 3: Explanatory Power (GFEVD) Across Variables



Notes: The GFEVD of each variable and model is averaged across 33 brands.

The overall findings can be summarized as follows. First, they emphasize the relevance of measuring consumer brand perceptions as both brand measures outperform the consumer mindset metrics in explaining firm value. Second, the GFEVD results indicate that complementing survey-based brand measures with real-time brand measures significantly improves the model's explanatory power.

5.4 Heterogeneity in the Complementary Effect

Although combining both brand measures displays the highest explanatory power on average, the level of improvement from the single-brand metric model to the dual-brand metric model is heterogeneous across brands (see Table 8).

Table 8: Explanatory Power (GFEVD) Across Brands

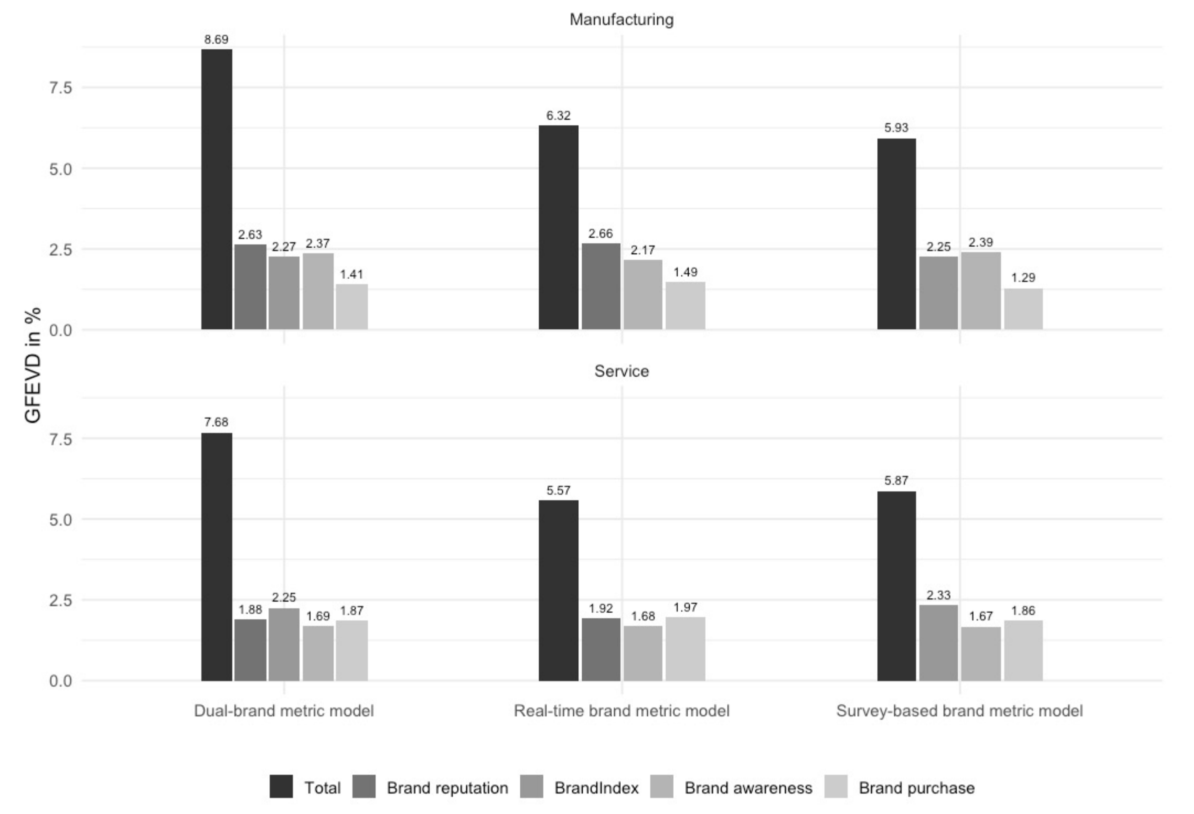
Brand	Dual-brand metric model	Real-time brand metric model	Survey-based brand metric model	Difference[a]	Improvement[b]	Type of good
1	9.87	8.06	8.55	1.32	15.44	Service
2	9.08	8.12	4.71	4.37	92.78	Manufacturing
3	3.22	2.83	1.40	1.82	130.00	Service
4	16.58	7.68	13.01	3.57	27.44	Manufacturing
5	4.77	3.89	3.03	1.74	57.43	Manufacturing
6	5.30	4.52	3.51	1.79	51.00	Service
7	8.31	5.23	4.85	3.46	71.34	Manufacturing
8	9.33	6.46	4.39	4.94	112.53	Service
9	6.22	3.14	4.96	1.26	25.40	Service
10	6.52	5.75	4.99	1.53	30.66	Manufacturing
11	7.75	7.28	6.22	1.53	24.60	Manufacturing
12	5.46	4.18	4.38	1.08	24.66	Service
13	2.59	2.20	2.54	0.05	1.97	Service
14	5.76	2.89	3.32	2.44	73.49	Manufacturing
15	11.85	6.66	7.44	4.41	59.27	Service
16	5.32	4.67	1.71	3.61	211.11	Manufacturing
17	2.29	1.69	0.75	1.54	205.33	Manufacturing
18	7.36	5.40	6.22	1.14	18.33	Service
19	15.63	9.85	14.20	1.43	10.07	Service
20	7.22	5.02	2.83	4.39	155.12	Service
21	11.65	10.98	9.72	1.93	19.86	Service
22	9.24	4.96	8.73	0.51	5.84	Manufacturing
23	8.64	7.69	8.00	0.64	8.00	Service
24	4.55	2.69	4.49	0.06	1.34	Manufacturing
25	22.89	17.03	16.33	6.56	40.17	Manufacturing
26	7.07	5.54	6.52	0.55	8.44	Manufacturing
27	8.27	3.45	7.07	1.20	16.97	Service
28	8.96	5.56	5.87	3.09	52.64	Service
29	11.47	11.06	4.32	7.15	165.51	Manufacturing
30	2.57	2.53	2.07	0.50	24.15	Service
31	5.12	4.77	4.38	0.74	16.89	Service
32	2.68	2.00	1.94	0.74	38.14	Service
33	13.99	10.48	12.01	1.98	16.49	Service

Notes: All values are percentages. [a] Difference in GFEVD between dual-brand metric model and survey-based brand metric model. [b] Calculated as the improvement from the survey-based brand metric model to dual-brand metric model. N(Manufacturing) = 14; N(Service) = 19.

While 13 brands show an improvement in explanatory power by over 50%, five brands display an improvement of less than 10%. The maximum improvement derived from adding the real-time brand measure to the model is over 211% for brand 16, which is a manufacturing brand. This finding underlines the need for a more systematic examination of differences between service and manufacturing brands.

Thus, Figure 4 displays the exploratory power of each model and variable across service and manufacturing brands. Although not statistically significant, the results suggest that the total explanatory power of the dual-brand and real-time brand metric models is higher for manufacturing than service brands. While the dual-brand metric model explains 8.69% of the variation in firm value for manufacturing brands, it only accounts for 7.68% of the variation for service brands. A similar pattern is observed for the real-time brand metric model, which accounts for 6.32% of the variation in firm value for manufacturing brands compared to 5.57% for service brands.

Figure 4: Explanatory Power (GFEVD) Across Types of Goods



Notes: The total GFEVD of firm value for each model is summed across all endogenous variables except past abnormal stock returns and averaged across 33 brands. The GFEVD of each variable is averaged across 33 brands.

The findings in Figure 4 further suggest that the higher total explanatory power of both models might be attributed to the higher explanatory power of the real-time brand measure for manufacturing brands. In the dual-brand metric model for manufacturing brands, the real-time brand measure (i.e., brand reputation) accounts for most of the explanatory power by explaining 2.63% of the variation in firm value. The survey-based brand measure (i.e., BrandIndex) accounts for only 2.27% of the variation. In contrast, the findings reverse for service brands, where the explanatory power of the survey-based brand measure exceeds that of the real-time brand measure (2.25% versus 1.88%). Furthermore, there is no notable difference in the explanatory power of the survey-based brand measure between manufacturing and service brands in the survey-based brand metric model. This finding underlines that survey-based brand measures are more comparable across brands in different product categories as they are standardized.

Finally, when looking at the average improvement from the survey-based brand metric model to the dual-brand metric model across brands, manufacturing brands show an increase in explanatory power of nearly 73% compared to 42% for service brands (see Table 9). Again, this difference is marginally insignificant ($p > 0.10$), which is unsurprising given the small sample size. Overall, the results suggest a directional support for the higher relevance of the real-time brand measure for manufacturing brands but lack statistical significance.

Table 9: Improvement in Explanatory Power Across Types of Goods

Type of good	Dual-brand metric model	Real-time brand metric model	Survey-based brand metric model	Difference[a]	Improvement[b]
Manufacturing	8.69	6.32	5.93	2.76	72.50
Service	7.68	5.57	5.87	1.81	41.90

Notes: All values are percentages. [a] Difference in GFEVD between dual-brand metric model and survey-based brand metric model. [b] Calculated as the improvement from the survey-based brand metric model to dual-brand the metric model. N(Manufacturing) = 14; N(Service) = 19.

6 Discussion

6.1 Summary and Discussion of Findings

In this article, I highlight the complementary effects of real-time and survey-based brand measures in explaining firm value. To do so, I refer to a recently developed theory-based real-time brand measure, the brand reputation tracker by Rust et al. (2021), and compare it to one of the most popular survey-based brand measures in the marketing literature, YouGov's BrandIndex. Both brand measures provide the advantage of being available at a highly granular level, specifically on a weekly basis. First, both measures are contrasted conceptually. Findings show that value and quality evaluations of the brand are important components of both brand measures. Other aspects, such as the brand's relationship with its stakeholders, are included in the brand reputation tracker but not in the BrandIndex. Thus, conceptually, both measures overlap slightly but also provide complementary components.

Model-free and model-based empirical analyses extend this initial theoretical comparison between the two brand measures. First, I find a low and negative correlation between the two brand measures. This finding aligns with prior research indicating a low and sometimes negative correlation between offline measures and their online counterparts (e.g., de Langhe, Fernbach, and Lichtenstein 2016).

Secondly, visual inspections of both brand measures show that they adequately reflect controllable marketing events (e.g., product introductions) and uncontrollable external events (e.g., negative news). However, differences may exist in terms of how fast and persistent the changes in the measures are in response to the event. For example, the decline in the BrandIndex time series of Facebook after the Cambridge Analytica Scandal persists until the end of the observation period, while the changes in the brand reputation time series revert back to the pre-event value (see Figure 2 Panel B). This finding supports the notion that survey-based attitudes are more enduring than online metrics (Pauwels and van Ewijk 2020).

In the second step, dynamic analyses based on VARX models and GFEVDs highlight the superiority of the model that includes both brand measures (i.e., the dual-brand metric model). On average, the dual-brand metric model exhibits the highest R^2 and GFEVD (dynamic R^2). While single-brand metric models, including either the real-time or the survey-based brand measure, perform similarly on average, the explanatory power improves by nearly 38% when combining the two brand measures in a single model. This highlights the complementary effect of real-time and survey-based brand measures, which both contribute to explaining firm value. However, the size of the complementary effect of both brand measures differs across brands depending on the type of good and is higher for manufacturing than for service brands. For service brands, survey-based brand measures have higher relevance, supporting previous research findings that emphasize the continued importance of survey-based attitude metrics (Pauwels and van Ewijk 2020).

6.2 Managerial Implications

From a managerial perspective, this research offers insights into what measures managers should consider for tracking consumer brand perceptions. The low correlation between real-time and survey-based brand measures highlights the danger of the current trend towards social media analytics (Fortune Business Insights 2025). Limiting brand perception tracking to consumer sentiment on social media may not capture longer-term consumer perceptions, thus leading to imprecise conclusions about brand health and firm performance.

The specific managerial implications are threefold. First, both real-time and survey-based brand measures contribute to explaining firm value. Thus, combining both brand measures yields the highest explanatory power, and managers are well advised to consider online and offline consumer sentiment simultaneously. Second, given the high costs of collecting survey data regularly, a selective brand tracking strategy might be appropriate. Managers could collect the more enduring survey data at a higher granularity (e.g., monthly) than real-time brand measures or decide whether to include survey data depending on the industry. The results of this article indicate that the explanatory power of both brand measures does not significantly differ when explaining firm value. If the focus is on stock market performance and budget constraints compel a choice between brand measures, selecting the more cost-effective real-time brand measure might be reasonable, especially for manufacturing brands, for which real-time brand measures provide higher explanatory power than survey-based brand measures. Third, there is a high correlation among the various survey-based metrics (i.e., BrandIndex and consumer mindset metrics). For example, monitoring survey-based brand perceptions is already a good indicator of brand purchase (see Table 7). On the other hand, the explanatory power of brand purchase in explaining firm value is relatively low (see Figure 3). Thus, firms can reduce data collection costs by focusing on only relevant metrics.

6.3 Theoretical Implications

This study contributes to the scarce literature comparing online and survey-based measures in two ways. First, this research adds to the literature by directly comparing two equivalent brand measures: a real-time and a survey-based brand measure. Previous research has investigated the link between online metrics and survey-based metrics by either relating online consumer sentiment about brands to survey-based consumer mindset metrics such as brand awareness (Colicev et al. 2018; de Vries, Gensler, and Leeflang 2017; Kübler, Colicev, and Pauwels 2020) or comparing those consumer mindset metrics to online consumer behavior such as website visits (Pauwels and van Ewijk 2020). The current research findings show that equivalent (social media-based) real-time and survey-based brand measures are complementary in explaining firm value.

In addition, graphical analyses of both brand measures align with the proposition that survey-based brand measures represent more enduring attitudes, whereas real-time brand measures are more likely to reflect contextual interest (Pauwels and van Ewijk 2020). Researchers should consider these differences between real-time and survey-based brand measures when conducting further studies. Depending on their research objective, they could consider including both brand measures in their analyses. Secondly, this article answers recent calls for research that test real-time brand measures against survey-based brand measures and links the former to firm performance outcomes (Marketing Science Institute 2022). Contrary to expectations, the results of this article underline that survey-based measures still matter but can be complemented with real-time brand measures.

6.4 Limitations and Directions for Future Research

The limitations of the current article can direct future research. For instance, the aggregated nature of the weekly data, which is based on the granularity of the brand reputation tracker, constitutes a limitation of the current work. Typically, social media data is available at a finer level, allowing researchers and practitioners to conduct real-time assessments of marketing actions, such as specific campaigns. Not considering these benefits might underestimate the true value of real-time brand measures in explaining firm performance (Pauwels and van Ewijk 2020). Future research working with more granular data can overcome this limitation. Second, current advancements in artificial intelligence may enable firms to develop more sophisticated text analysis tools (Newman 2019), which better recognize complex languages (e.g., sarcasm) and further enhance the value of real-time brand measures. I encourage future research to update this work as new real-time brand measures based on more advanced sentiment extraction tools arise. This article examines the brand's stock market performance as a financial performance metric. Extending the findings to sales data might increase generalizability. Finally, in light of recent restrictions imposed on the application of X (formerly Twitter) data in research and practice (Ledford 2023; Milmo 2023), the transferability of the findings to other social media platforms (e.g., Meta's Threads) is of high interest.

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Appendix Paper 3

In this Appendix, I provide the following information:

1) Appendix A: Details on the YouGov Data
2) Appendix B: Model-Free Evidence
3) Appendix C: Steps of the VARX model estimation
4) Appendix D: Brand-level results of the VARX models

Appendix A: Details on the YouGov Data

Data collection procedure. YouGov, a global market research company, provides data on three types of metrics: media and communication metrics, purchase funnel metrics, and brand perception metrics. The first two types of metrics capture the consumer decision journey and provide information on consumer mindset metrics such as awareness, consideration, and purchase intention (see Table A1 for the exact questions). YouGov monitors over 1,900 brands from 44 sectors in the U.S. market by surveying 5.500 consumers daily (as of June 2023). First, respondents select all brands they know. This query constitutes the awareness measure. In the following, respondents answer questions regarding the remaining metrics by selecting all brands with which they agree with the respective statement, e.g., "Of the brands considered, which are you most likely to purchase?" for purchase intention. To measure the BrandIndex dimensions, YouGov follows a strategy where respondents must categorize brands into positive or negative statements for each dimension. For example, for the value dimension, respondents select all the brands they agree with on the positive statement (Which of the following brands do you think represents *good* value for money?) and on the negative statement (Which of the following brands do you think represents *poor* value for money?). The overall value score for a specific brand is then calculated by subtracting the number of respondents who selected the brand for the negative statement from the number of respondents who selected the brand for the positive statement and dividing it by the total number of respondents ([number of positive – number of negative]/ total number of respondents). The final scores range from -100 to +100. I downloaded the data at the daily level and then aggregated it to weekly data.

Variable operationalization. There are two options to select from when constructing the variables based on YouGov metrics: total and aware scores. For the total score, respondents who are not familiar with the brand and do not select it in the awareness question at the beginning are classified as neutral. The number of total respondents is then calculated as the number of positives + the number of negatives + the number of neutrals. For the aware score, only respondents who know the brand are considered (i.e., the total number of respondents = the number of positives + the number of negatives). As the brand reputation tracker builds on user-generated content (UGC) on X (formerly Twitter), and only users who know the brand post about it, the BrandIndex measure in this research builds on the aware scores for each brand. Similarly, the brand purchase metrics build on the aware scores. On the contrary, the brand awareness metrics use the total scores and are indicated as percentages from 0-100%.

Table A1: Questions for the Mindset Metrics

Mindset metrics	YouGov metrics	Questions
Brand awareness	Aided awareness	Which of the following brands have you ever heard of?
	Advertising awareness	Which of the following brands have you seen an advertisement for in the past two weeks?
Brand purchase	Purchase intent	Of the brands considered, which one are you most likely to purchase?
	Consideration	When you are in the market next to make a purchase, which brands would you consider?
	Current customer	Which brands have you recently purchased/currently own?

Notes: The specific questions of the YouGov dimensions are from June 2023.

Following past research (Colicev et al. 2018; Valenti et al. 2023), I construct the consumer mindset metrics as the average of several YouGov metrics based on the factor analysis results with varimax rotation across brands. The results in Table A2 highlight a two-factor solution with all factor eigenvalues higher than 1 and each YouGov metric loading higher on one of the factors than the other. The correlations and the reliability of the constructed mindset variables are presented in Table A3.

Table A2: Variance Explained and Factor Loadings by Each Factor Across Brands

	Brand Purchase	Brand Awareness
	Factor 1	Factor 2
	(2.429)	(1.530)
Purchase intent	**0.825***	0.393
Consideration	**0.924***	0.263
Current customer	**0.812***	0.354
Awareness	0.399	**0.513***
Advertising awareness	0.278	**0.958***

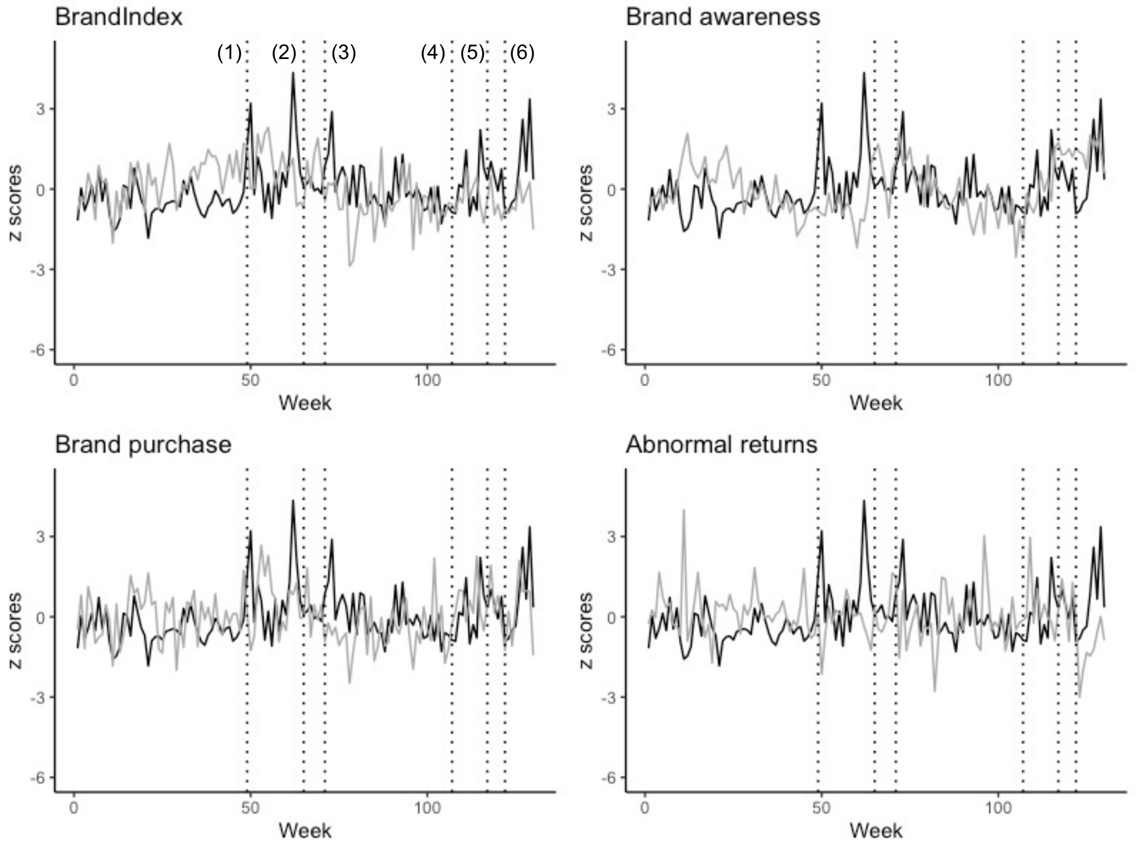
Notes: Eigenvalues (greater than 1) for each factor are reported in parenthesis below the factor. All values are across brands. *Indicates the highest loading.

Table A3: Correlations and Reliability of Each Construct Across Brands

	Brand Purchase	Brand Awareness
Cronbach alpha	**0.90**	**0.74**
Purchase Intent	0.91	–
Consideration	0.92	–
Current Customer	0.88	–
Awareness	–	0.70
Ad Awareness	–	0.70

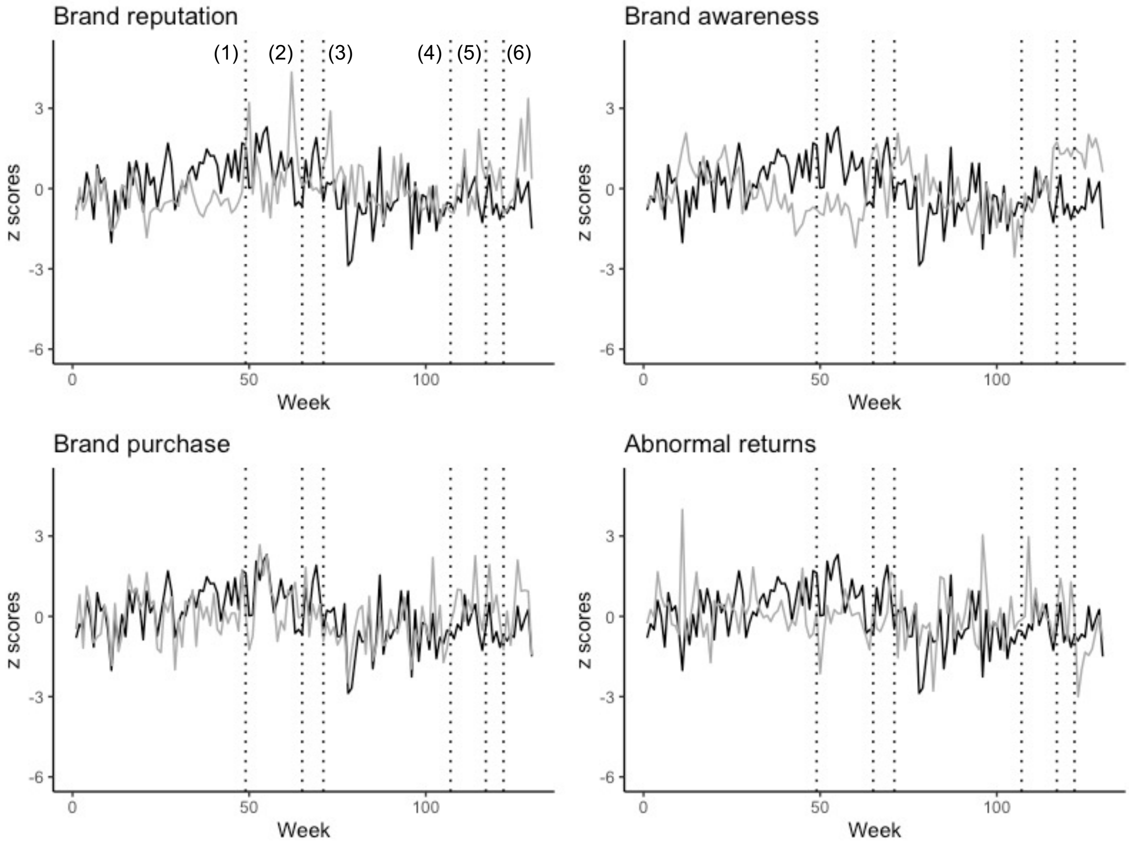
Appendix B: Model-Free Evidence

Figure A1: Time Series of Apple's Brand Reputation



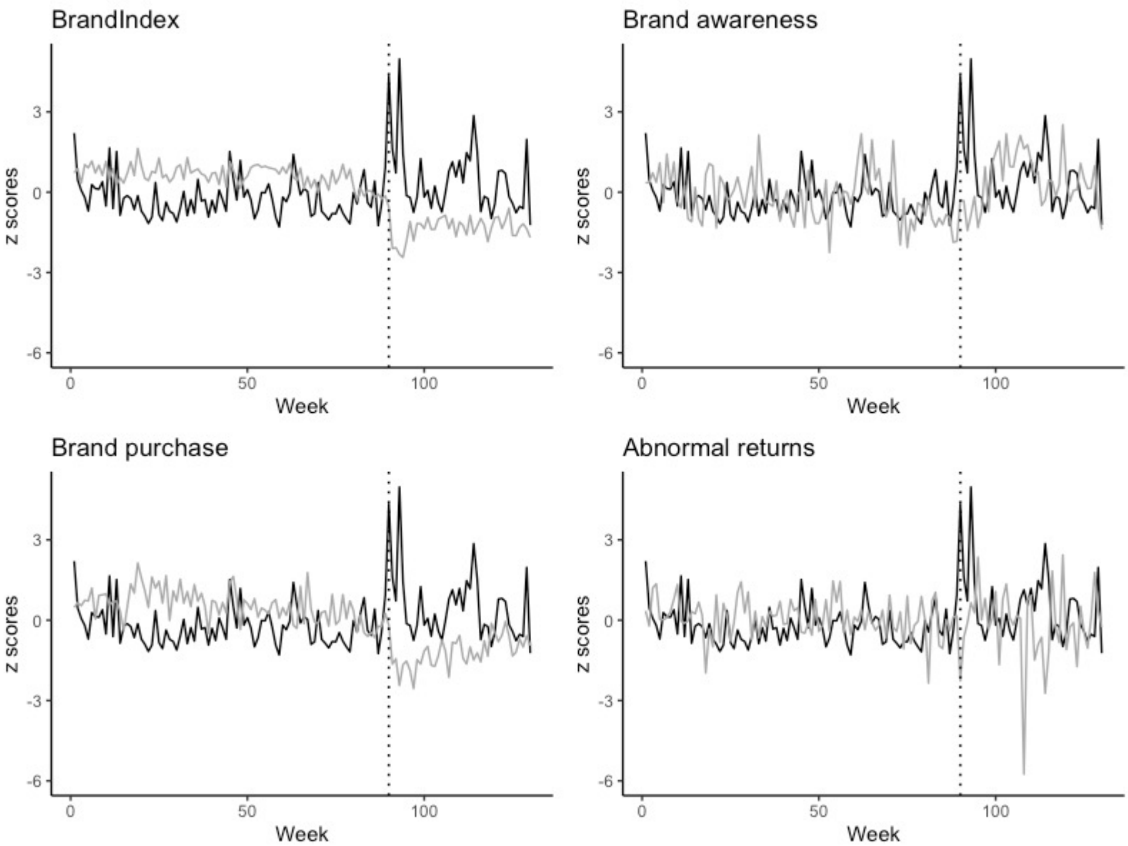
Notes: The black line represents the standardized time series for Apple's brand reputation, while the grey lines represent the standardized time series for BrandIndex, brand awareness, brand purchase, and abnormal stock returns. The dotted lines are Apple's product introduction events (introduction of (1) iPad Pro, MacBook, (2) iMac, iPhone 8, Apple Watch, (3) iPhone X, (4) MacBook Pro, (5) iPhone XS, Apple Watch, and (6) iPhone XR).

Figure A2: Time Series of Apple's BrandIndex



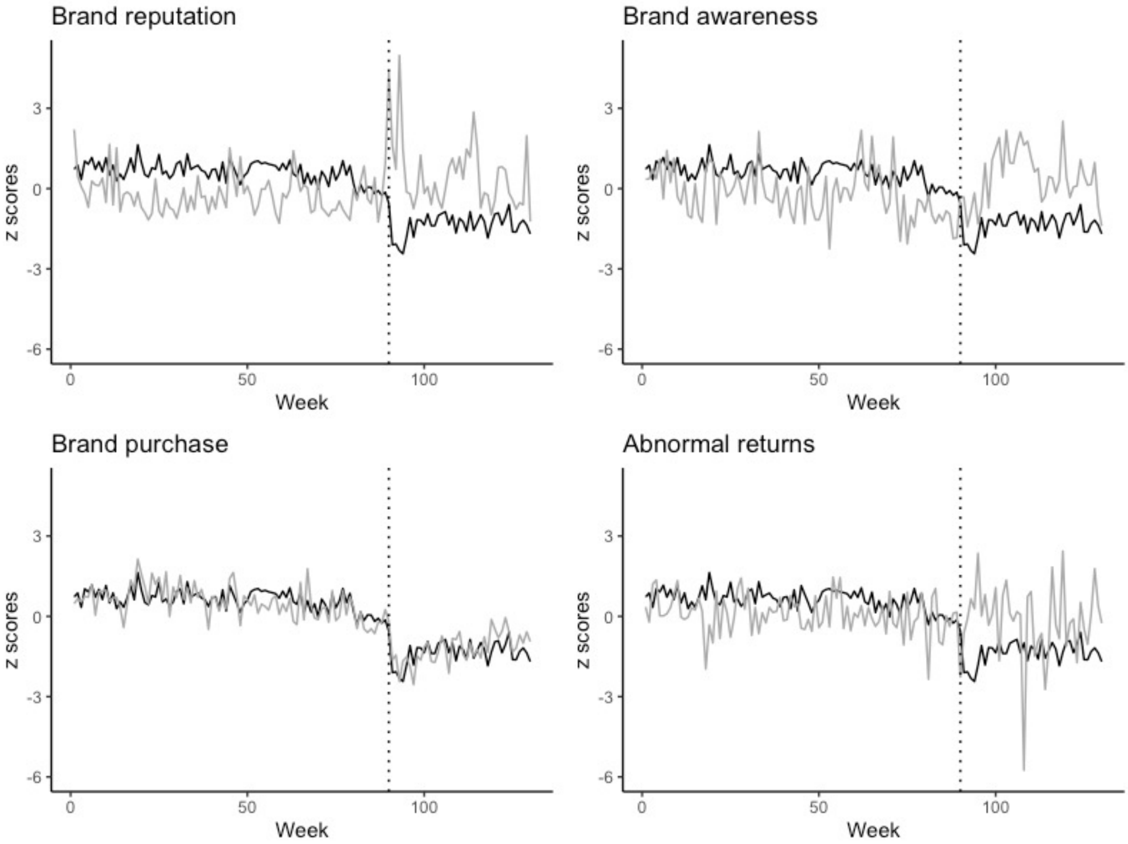
Notes: The black line represents the standardized time series for Apple's BrandIndex, while the grey lines represent the standardized time series for brand reputation, brand awareness, brand purchase, and abnormal stock returns. The dotted lines are Apple's product introduction events (introduction of (1) iPad Pro, MacBook, (2) iMac, iPhone 8, Apple Watch, (3) iPhone X, (4) MacBook Pro, (5) iPhone XS, Apple Watch, and (6) iPhone XR).

Figure A3: Time Series of Facebook's Brand Reputation



Notes: The black line represents the standardized time series for Facebook's brand reputation, while the grey lines represent the standardized time series for BrandIndex, brand awareness, brand purchase, and abnormal stock returns. The dotted line represents the Cambridge Analytica Scandal in March 2018.

Figure A4: Time Series of Facebook's BrandIndex



Notes: The black line represents the standardized time series for Facebook's BrandIndex, while the grey lines represent the standardized time series for brand reputation, brand awareness, brand purchase, and abnormal stock returns. The dotted line represents the Cambridge Analytica Scandal in March 2018.

Appendix C: Steps of the VARX Model Estimation

Unit root tests

To decide whether the variables are stationary or display a unit root, augmented Dickey-Fuller (ADF) unit root tests are performed for each explanatory variable and each brand separately. Following Enders (2004), I apply an iterative process, which starts the unit root testing with a deterministic trend and a drift, and subsequently removes the deterministic trend and drift component if not significant. This procedure minimizes the risk of falsely accepting the presence of a unit root due to misspecifications of the unit root test if the data-generating process is unknown. To further avoid erroneous conclusions about the presence of a unit root, I additionally visually inspect the time series of each explanatory variable for the presence of structural breaks and apply the Zivot and Andrews (1992) unit root test for structural breaks, if applicable. Following this procedure, approximately 72% of the brands in the given sample (33 brands out of 46 brands) contain no unit root. To increase comparability across brands for further analyses, I follow past research and only analyze brands where all explanatory variables are stationary (Srinivasan, Vanhuele, and Pauwels 2010). Thus, all variables enter the VARX models in levels, and the reported results are averaged across the 33 brands.

Granger Causality

To establish the dynamic relationship among the explanatory variables, pairwise Granger causality tests (Granger 1969) are performed. Granger causality of a variable Y by a variable X signals that Y can be better predicted by including past values of X in addition to past values of Y. I use the Dumitrescu and Hurlin (2012) panel causality test, which accounts for brand-specific heterogeneity and provides an overall test statistic by averaging across brands. To avoid false conclusions, I follow past research (Pauwels and van Ewijk 2020; Trusov, Bucklin, and Pauwels 2009) and test lags from 1 to 13 (i.e., one quarter) and report the results of the lag with the lowest p-value (see Table A4).

Table A4: Granger Causality Test Results

Response to	Brand reputation	BrandIndex	Brand awareness	Brand purchase	Abnormal returns
Brand reputation	–	0.000	0.019	0.046	0.175
BrandIndex	0.037	–	0.000	0.000	0.202
Brand awareness	0.007	0.000	–	0.038	0.045
Brand purchase	0.001	0.024	0.009	–	0.080
Abnormal returns	0.002	0.166	0.308	0.021	–

Notes: Minimum p-value across 13 lags (i.e., one quarter). The null hypotheses assume that the variables on the left column do not Granger cause the variables in the top row. The results are based on the panel Granger causality test by Dumitrescu and Hurlin (2012). Includes only the brands with stationary variables (N = 33).

Optimal lag selection

The optimal lag for each VARX model is determined according to the Akaike information criterion (AIC) and controlling for autocorrelation bias using the Breusch-Godfrey LM test for serial correlation (Breusch 1978; Colicev et al. 2018; Godfrey 1978). First, the optimal lag is determined based on AIC. If the model with the proposed optimal lag length by AIC (with max. lag length 5) displays serial correlation, I test additional models up to five lags and add lags if the model’s serial correlation can be improved (Colicev et al. 2018; Franses 2005). If the model’s serial correlation does not improve when adding lags up to lag 5, I use the lag length proposed by AIC for parsimony. As the number of lags influences the model’s explanatory power (Leeflang et al. 2017), the lag selection is optimized for all three VARX models simultaneously so that the best common lag is selected.

Observation-to-parameter ratio

Table A5 displays the number of parameters and the observation-to-parameter ratio for the dual-brand metric VARX models. As some brands do not contain any dividend announcements, M&A announcements, or structural breaks during the observation period, the number of parameters in the VARX model for the same lag length can differ between brands. If all control variables are included in the model and the optimal lag length is 1 (e.g., Brand 7), the number of parameters per equation is 13. This contains five lagged endogenous variables, an intercept, a deterministic trend, and six control variables. As a result, the observation-to-parameter ratio equals 9.29 (129 observations). Across brands, the average observation-to-parameter ratio is 9.70, which exceeds the minimum suggested threshold of 5 (Leeflang et al. 2015).

Table A5: Overview of VARX Model Specifications

Brand	Lag	DVcount	MAcount	Break	Parameters	Observation-to-parameter ratio
1	2	yes	no	no	16	8.00
2	2	yes	yes	no	17	7.53
3	1	yes	yes	no	12	10.75
4	1	no	yes	no	11	11.73
5	1	yes	no	no	11	11.73
6	1	yes	no	no	11	11.73
7	1	yes	yes	yes	13	9.92
8	3	no	yes	yes	22	5.77
9	1	yes	yes	no	12	10.75
10	1	yes	yes	no	12	10.75
11	1	yes	no	no	11	11.73
12	1	no	yes	yes	12	10.75
13	1	yes	yes	yes	13	9.92
14	2	yes	no	no	16	8.00
15	3	yes	yes	no	22	5.77
16	1	yes	yes	no	12	10.75
17	1	yes	yes	no	12	10.75
18	1	yes	yes	no	12	10.75
19	2	yes	yes	no	17	7.53
20	1	yes	no	no	11	11.73
21	2	yes	yes	no	17	7.53
22	1	yes	yes	yes	13	9.92
23	2	yes	yes	no	17	7.53
24	1	yes	yes	no	12	10.75
25	3	no	yes	yes	22	5.77
26	1	yes	yes	no	12	10.75
27	1	yes	yes	no	12	10.75
28	1	yes	yes	no	12	10.75
29	1	yes	yes	no	12	10.75
30	1	no	yes	no	11	11.73
31	1	yes	yes	no	12	10.75
32	1	yes	yes	no	12	10.75
33	3	no	yes	no	21	6.05
Average	1.42				13.94	9.70

Notes: Parameters indicate the number of parameters in the dual-brand metric model as this is the model with the highest number of variables. DVcount = count variable for dividend announcements; MAcount = count variable for M&A announcements; Break = dummy variable 1 if structural break included, 0 otherwise.

Appendix D: Brand-Level Results of the VARX Models

Estimation of separate VARX models

I estimate separate VARX models for each brand instead of applying a panel VAR approach for three reasons. First, panel VAR models are more appropriate for datasets with a large number of cross-sections and short time series as this allows exploiting cross-sectional heterogeneity when estimating the model parameters. In contrast, I have a long time series of 130 periods and a relatively small number of cross-sections (33 brands). This facilitates the estimation of individual models for each brand. Second, one of the main objectives of this research is to identify heterogeneity in the complementary effects of real-time and survey-based brand measures across brands. Incorporating moderation effects in VARX models is not possible. Estimating models for each brand individually overcomes this limitation by comparing brand-specific results in a second-stage analysis. Finally, the VARX model specifications might differ across brands as some brands do not contain any dividend or M&A announcements during the observation period. Brand-specific models can flexibly account for these differences (Colicev et al. 2018).

The brand-level VARX models and their respective GFEVDs are estimated using the vars (v1.6-1; Pfaff 2008) and Spillover packages (v0.1.1; Urbina 2025) in R v4.4.1 (R Core Team 2025). Additionally, I used ChatGPT-3.5 and ChatGPT o4-mini-high (versions from February 2023 to May 2025; OpenAI 2025) to generate, enhance, and streamline code, such as creating loops over brands for estimating brand-level VARX models.

Tables A6 to A10 display the individual brand-specific R^2 and GFEVD results for all three models. Additionally, Tables A7 to A9 display the relative importance of each variable in explaining firm value in each model.

Brand-level R^2 results

Table A6: Brand-Level R^2 Results

Brand	Dual-brand metric model	Real-time brand metric model	Survey-based brand metric model
1	0.114	0.086	0.113
2	0.223	0.223	0.188
3	0.079	0.064	0.068
4	0.155	0.080	0.123
5	0.092	0.091	0.085
6	0.065	0.065	0.065
7	0.108	0.105	0.077
8	0.163	0.142	0.139
9	0.134	0.115	0.128
10	0.074	0.074	0.058
11	0.059	0.056	0.056
12	0.053	0.053	0.050
13	0.065	0.065	0.063
14	0.110	0.103	0.101
15	0.219	0.183	0.195
16	0.096	0.091	0.076
17	0.063	0.062	0.059
18	0.067	0.066	0.060
19	0.165	0.131	0.154
20	0.161	0.137	0.117
21	0.227	0.195	0.213
22	0.100	0.057	0.097
23	0.089	0.085	0.088
24	0.156	0.139	0.156
25	0.262	0.186	0.218
26	0.053	0.053	0.053
27	0.069	0.069	0.068
28	0.072	0.020	0.071
29	0.081	0.078	0.073
30	0.042	0.040	0.042
31	0.118	0.115	0.117
32	0.118	0.117	0.115
33	0.191	0.137	0.175
Average	0.116	0.099	0.105

Brand-level GFEVD results

Table A7: Brand-Level GFEVD Results for the Dual-Brand Metric Model

Brand	Brand reputation	BrandIndex	Brand awareness	Brand purchase	Total
1	1.83	2.45	5.39	0.20	9.87
2	4.44	0.94	2.01	1.68	9.08
3	1.89	0.41	0.43	0.50	3.22
4	3.68	7.94	3.85	1.11	16.58
5	1.95	1.06	0.94	0.82	4.77
6	1.87	0.84	1.34	1.25	5.30
7	3.40	3.28	0.96	0.67	8.31
8	5.80	1.68	1.12	0.74	9.33
9	1.31	3.14	1.01	0.76	6.22
10	2.08	0.76	2.78	0.91	6.52
11	1.62	0.77	1.37	3.99	7.75
12	1.16	1.26	0.91	2.12	5.46
13	0.12	0.41	1.62	0.45	2.59
14	2.25	2.71	0.07	0.73	5.76
15	4.64	5.73	0.72	0.75	11.85
16	2.91	0.36	1.99	0.07	5.32
17	1.33	0.52	0.03	0.41	2.29
18	0.63	2.06	2.63	2.04	7.36
19	1.37	7.02	1.87	5.36	15.63
20	3.87	2.10	0.87	0.38	7.22
21	1.70	0.61	0.92	8.42	11.65
22	0.21	4.05	4.75	0.24	9.24
23	0.55	0.89	3.63	3.58	8.64
24	0.08	1.57	0.49	2.40	4.55
25	4.86	6.31	9.38	2.35	22.89
26	0.53	1.21	1.21	4.13	7.07
27	1.23	5.04	0.25	1.76	8.27
28	3.28	4.73	0.31	0.64	8.96
29	7.48	0.30	3.39	0.29	11.47
30	0.54	0.03	0.58	1.42	2.57
31	0.77	0.76	3.15	0.44	5.12
32	0.75	0.80	1.05	0.08	2.68
33	2.40	2.74	4.30	4.55	13.99
Average	2.20	2.26	1.98	1.67	8.11

Table A8: Brand-Level GFEVD Results for the Real-Time Brand Metric Model

Brand	Brand reputation	Brand awareness	Brand purchase	Total
1	2.28	5.63	0.15	8.06
2	4.52	1.92	1.69	8.12
3	1.95	0.45	0.43	2.83
4	4.00	3.30	0.38	7.68
5	2.07	0.95	0.87	3.89
6	1.90	1.36	1.26	4.52
7	3.54	0.97	0.72	5.23
8	4.60	0.68	1.18	6.46
9	1.51	1.05	0.59	3.14
10	2.08	2.77	0.90	5.75
11	1.70	1.40	4.19	7.28
12	1.18	0.90	2.10	4.18
13	0.11	1.63	0.45	2.20
14	2.15	0.06	0.68	2.89
15	4.98	0.88	0.80	6.66
16	2.60	1.94	0.12	4.67
17	1.25	0.03	0.40	1.69
18	0.66	2.64	2.09	5.40
19	1.38	1.73	6.75	9.85
20	3.99	0.66	0.36	5.02
21	1.82	0.87	8.29	10.98
22	0.15	4.59	0.22	4.96
23	0.74	3.48	3.47	7.69
24	0.09	0.37	2.22	2.69
25	5.10	7.65	4.28	17.03
26	0.52	1.12	3.90	5.54
27	1.32	0.24	1.90	3.45
28	3.83	0.69	1.05	5.56
29	7.42	3.35	0.30	11.06
30	0.54	0.56	1.43	2.53
31	0.93	3.41	0.43	4.77
32	0.78	1.13	0.08	2.00
33	2.00	3.86	4.62	10.48
Average	2.23	1.89	1.77	5.89

Table A9: Brand-Level GFEVD Results for the Survey-Based Brand Metric Model

Brand	BrandIndex	Brand awareness	Brand Purchase	Total
1	2.67	5.75	0.12	8.55
2	0.62	2.71	1.37	4.71
3	0.39	0.51	0.51	1.40
4	8.33	4.29	0.39	13.01
5	1.23	1.00	0.80	3.03
6	0.87	1.37	1.27	3.51
7	3.06	1.19	0.60	4.85
8	2.54	0.96	0.88	4.39
9	3.00	1.15	0.81	4.96
10	0.88	3.24	0.87	4.99
11	0.68	1.54	4.01	6.22
12	1.36	0.86	2.17	4.38
13	0.38	1.62	0.54	2.54
14	2.64	0.08	0.60	3.32
15	6.06	0.60	0.78	7.44
16	0.24	1.46	0.01	1.71
17	0.43	0.03	0.29	0.75
18	2.21	2.12	1.89	6.22
19	7.27	1.81	5.12	14.20
20	2.21	0.47	0.15	2.83
21	0.63	0.66	8.43	9.72
22	3.97	4.51	0.25	8.73
23	0.80	3.59	3.61	8.00
24	1.57	0.49	2.43	4.49
25	6.30	8.11	1.91	16.33
26	1.19	1.19	4.14	6.52
27	5.08	0.23	1.76	7.07
28	4.84	0.33	0.70	5.87
29	0.35	3.64	0.33	4.32
30	0.03	0.60	1.44	2.07
31	0.67	3.21	0.50	4.38
32	0.79	1.06	0.09	1.94
33	2.57	4.86	4.58	12.01
Average	2.30	1.98	1.62	5.89

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