ECONOMETRIC ESSAYS ON PROTECTING, GROWING, AND BENEFITING FROM CUSTOMER-BASED BRAND EQUITY

Inauguraldissertation

zur

Erlangung des Doktorgrades

der Wirtschafts- und Sozialwissenschaftlichen Fakultät

der Universität zu Köln

2016

vorgelegt von

Diplom-Kaufmann Max Philipp Backhaus

aus

Mainz

Referent: Prof. Dr. Marc Fischer

Koreferent: Prof. Dr. Franziska Völckner

Tag der Promotion: 12.01.2017

ACKNOWLEDGEMENTS

The present dissertation was written during my time as research assistant at the Chair for Marketing and Market Research at the Universtity of Cologne. I would like to express my sincere gratitude to the holder of the chair, Professor Dr. Marc Fischer, who intruduced me to the topic of customer-based brand equity and guided me through this thesis. I highly respect his professional instruction and the way how he has pushed me forward.

I would also like to thank the co-examiner Professor Dr. Franziska Völckner for her careful and detailed examination as well as Professor Dr. Reinartz for being the head of the examination committee on the day of my disputation. My work has benefitted greatly from the suggestions of my colleagues at the Chair for Marketing and Market Research, namely Prof. Dr. Alexander Himme, Dr. Thomas Schollmeyer, Dr. Tobias Hornig, Dr. Alexander Edeling, Eric Lennartz, Samuel Stäbler, and Birte Terlinden. Thank you for enabling me to work in an encouriging and inspiring working environment. I am also very thankful for the unlimited support by the very soul of our team Christa Körner.

Furthermore, I would like to offer some special thanks to all other colleagues of the Marketing Area at the University of Cologne. Particularly, to my colleague and friend Maren Becker; I highly value the discussions we have had.

Besides, there are many people who have accompanied me throughout the last 5 years and supported me whenever needed. Conducting research is sometimes lonely, but I am happy to have people who let me shut down the computer for a while and who also give me something else to think about. Therefore, warm thanks to my boys for all the great times we have had during the last years.

There have been days when I have doubted and not had any idea where I will end up with my research and this dissertation. Nonetheless during the last ten years of studies and work I have always had something stable in my life: a person who believes in me and my abilities, who makes me to continue to follow my goals and who gives me faith, strength, and love. My most sincere thanks go to that person, Kati.

Finally, I dedicate this thesis to my parents Barbara and Klaus Backhaus. You give me all the opportunities for accomplishing my dreams. I owe my life to your constant love, encouragement, and moral support. You have made me who I am today.

CONTENTS

LIST OF FIGURES

SYNOPSIS

PAPER I: BRAND DAMAGE FROM PRODUCT HARM AND CORPORATE SOCIAL IRRESPONSIBILITY - HOW DEEP AND HOW LONG?

PAPER II: DO LAYOFFS HURT A FIRM'S BRAND? - AN EVENT STUDY WITH CONSUMER MINDSET METRICS

PAPER III: HOW DO BRANDS GENERATE VALUE FOR INVESTORS? - IT'S FROM NEW BUSINESS AND COMPETITIVE ADVANTAGE

LIST OF TABLES

SYNOPSIS

PAPER I: BRAND DAMAGE FROM PRODUCT HARM AND CORPORATE SOCIAL IRRESPONSIBILITY - HOW DEEP AND HOW LONG?

PAPER II: DO LAYOFFS HURT A FIRM'S BRAND? - AN EVENT STUDY WITH CONSUMER MINDSET METRICS

PAPER III: HOW DO BRANDS GENERATE VALUE FOR INVESTORS? - IT'S FROM NEW BUSINESS AND COMPETITIVE ADVANTAGE

SYNOPSIS

1 Overview

This dissertation thesis is about brands and the value they provide to their firms. Brands have been object of a broad stream of research as well as popular literature. Despite these facts the brand arena is still under research. We need more insights on how to build, protect, benefit, and grow from customer-based brand equity (CBBE). On this background the dissertation comprises three research papers, each addressing distinct questions with respect to antecedents and outcomes of CBBE. Therefore, the thesis addresses topics of the brand research field that are still waiting to be answered. Specifically, two of the three papers investigate how firm behavior can endanger tediously built brand values. Paper I examines the impact of product-harm and corporate social irresponsibility crises on consumer brand attention and brand strength. It also reveals the role of firm- and crisis-specific moderators that attenuate or amplify the effect of crises on brands. The second paper assesses whether firms' layoff announcements affect consumer mindset metrics. In addition to brand attention and brand strength, the paper also accounts for a volatility-based metric, namely brand rating dispersion. Paper III analyzes how CBBE in turn affects different routes of firm value growth from the investor's perspective. That is, it assesses the magnitude of the effects of advertising and CBBE on firm value drivers.

Overall, the dissertation contributes to the scientific knowledge enhancement with respect to two fundamental issues of strategic marketing mentioned also as MSI research priorities for 2014-2016. First, it refines the understanding of optimal social contracts with consumers: "*Consumer expectations have risen in terms of what they think firms should be doing besides selling their products and services. Violations of these expectations can have severe consequences, as many firms are discovering*" (MSI 2014). Paper I and II underline the threat of consumer expectations with regard to firms' social behavior. They also generate insights that facilitate optimal firm reactions in cases when such behavior is discussed negatively within the media. Second, the dissertation thesis generates detailed insights into how CBBE affects future firm value growth. Thereby, it contributes to the challenge of measuring and communicating the value of marketing activities and investments (MSI 2014).

Table 1 presents an overview of the three articles including author and publication-status information.

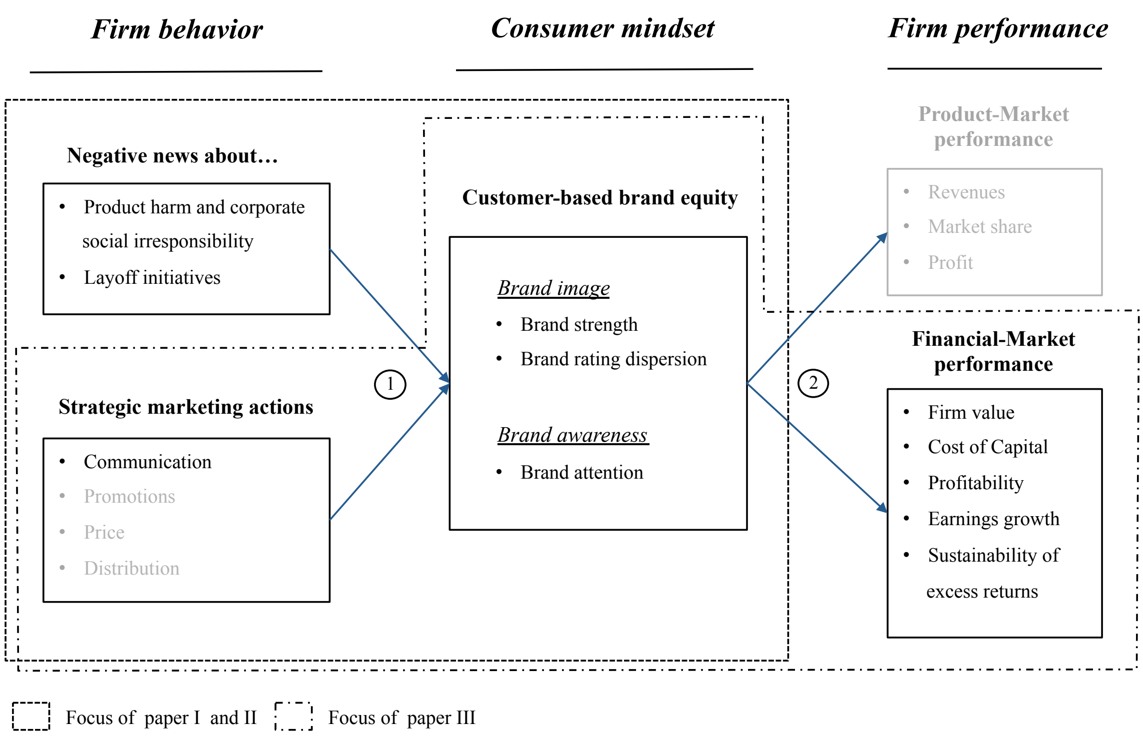
Table 1: Overview of Dissertation Projects

Paper	*Title*	*Author(s)*	*Status*
I	Brand Damage from Product Harm and Corporate Social Irresponsibility – How deep and how long?	Max Backhaus and Marc Fischer	Under review (2nd round): *Journal of Marketing Research*
II	Do Layoffs Hurt a Firm's Brand? – An Event Study with Consumer Mindset Metrics	Max Backhaus	Prepared to submit to: *Journal of Marketing*
III	How Do Brands Generate Value for Investors? - It's from New Business and Competitive Distinctiveness	Marc Fischer, Max Backhaus, and Tobias Hornig	Under review (1st round): *Management Science*

2 Introduction

Customer-based brand equity (CBBE) is a central if not the most important intangible asset for many firms (Keller 2008). It often takes years and large, specific investments for firms to build strong brands. High values in CBBE, which originate in the minds and perceptions of consumers (Keller 1993), can assist firms in refining their product-market performance and eventually lead to better financial performance (Edeling and Fischer 2016; Katsikeas et al. 2016). Consequently, it is of key relevance to (1) understand whether and how firms can effectively build and protect CBBE and (2) to investigate how exactly CBBE drives the financial-market performance of firms. Accordingly, the present dissertation focuses on these two main topics. The conceptual framework in Figure 1 summarizes and positions the three econometric studies accordingly.

Figure 1: Conceptual Framework and Classification of Dissertation Projects



On the one hand, (1) brand investments are threatened if brand equity and brand perception are endangered to get damaged. That is why companies should know about effective mechanism that drive the effects. Negative news about firm behavior may severely harm the trust and confidence consumers place in brands (Ahluwalia, Burnkrant, and Unnava 2000). The increasing complexity of products, more stringent product-safety legislation, an increasing internationalization across the supply chain and production of products combine to make corporate, brand, and product crises even more frequent events (Cleeren, van Heerde, and Dekimpe 2013). Although academic literature supports a general impact of crises on brands, important aspects have largely been ignored (Backhaus and Fischer 2016). First, different types of events may have different magnitude in impact. Second, effects may also differ with respect to their persistence, and third, crisis situations are commonly at first ex-post defined as an actual crisis creating a fundamental endogeneity problem. To benefit from marketing investments and high levels in brand value it should, therefore, be the key focus for researchers and managers to better understand the threats from negative media coverage about firm behavior to consumer brand perceptions. Consequently, an investigation of attenuating and amplifying impact drivers is warranted. In order to protect brands firms need to react properly to each specific situation and adjust their strategic marketing actions accordingly. The first two essays of this dissertation focus on enhancing the understanding of the effect of news about firm behavior on consumers.

The first paper, titled "Brand Damage from Product Harm and Corporate Social Responsibility – How Deep and How Long?" is co-authored by Max Backhaus and Marc Fischer. It comprises a comprehensive investigation of the dynamic impact of different crisis events stemming from product harm and corporate social irresponsibility (CSI) on consumer-based brand attention and brand strength. The empirical study is based on a unique dataset of 214 crisis events across 12 industries, 69 brands, and 5 years of weekly brand perception data.

Paper II, titled "Do Layoffs Hurt a Firm's Brand? – An Event Study with Consumer Mindset Metrics" (by Max Backhaus) quantifies the effects of layoff announcements on consumer brand perceptions. Here, the author also accounts for a volatility-based metric named brand rating dispersion, since heterogeneity in consumer brand perceptions also endangers brand values. Furthermore, the study extends the common event study methodology to consumer mindset metrics as the dependent variable[1] and shows that layoffs indeed affect consumer brand perceptions.

On the other hand, (2) building strong brands requires huge financial resources and marketing mangers are under increasing pressure to prove the financial impact of their investments (Edeling and Fischer 2016). Specifically, marketing expenditures are among the

[1] Classical event studies usually focus on abnormal changes in stock returns as the dependent variable.

first to be cut when the economic situation worsens as in the recent global economic crisis (Van Heerde et al. 2013). However, investment managers are rather looking for credible strategies for value-creating growth than for excess cash-payouts by firms (Ghesquieres et al. 2016). While extant research at the marketing and finance interface demonstrates the value relevance of marketing (Srinivasan and Hanssens 2009), we know little about the manner in which value is generated. Hence, there is no longer doubt *that* (successful) marketing contributes to firm value, but it is not clear *how* it generates the value.

Paper III, titled "How Do Brands Generate Value for Investors? - It's from New Business and Competitive Distinctiveness" is co-authored by Marc Fischer, Max Backhaus, and Tobias Hornig. In this study the authors decompose firm value into its core financial drivers from an investor perspective to empirically investigate the different routes of value generation of marketing expenditures mediated by CBBE based on a sample of 613 firms over 9 years.

The next section summarizes motivation, research objectives, main results, and implications of each dissertation project.

3 Summary of Dissertation Projects

3.1 Paper I: Brand Damage From Product Harm And Corporate Social Irresponsibility – How Deep And How Long?

Brand equity can suffer significantly during a crisis (e.g., product-harm crisis or environmental scandal), with profound and enduring effects on subsequent corporate performance (Cleeren, van Heerde, and Dekimpe 2013). Samsung's Galaxy Note 7 recall in August 2016 due to battery faults, Volkswagen's "Dieselgate" in 2015, or BP's Deepwater horizon oil spill in 2010 are only a few examples where companies were discussed negatively within the press. The increasing complexity of products, more stringent product-safety legislation, an increasing internationalization across the supply chain and production, as well as the growing importance of ethically correct behavior combine to make corporate, brand, and product crises even more frequent events (Dawar and Pillutla 2000).

Managers understand the threat of a product failure to marketing assets and economic performance but seem to be less concerned about brand damage from corporate social misbehavior such as bribery. Corporate misconduct is not as tangible as a product-harm crisis where the operational reliability or product safety is affected. This makes it difficult to infer how consumers respond to the breach of rules and moral standards. Nevertheless, behavior-related crisis are covered in leading media as frequently as product-harm events (Bazerman and Tenbrusel 2011). An extensive amount of literature exists that focuses mainly on one specific crisis situation, namely product-harm crises, but not much is known about the effects of corporate social irresponsibility events (Kang, Germann, and Grewal 2016). Many studies simply do not differentiate between different crisis causes and focus on hypothetical crisis events in experimental or survey-based settings (Backhaus and Fischer 2016). Although these studies offer valuable insights, the external validity is limited by the usual shortcomings of experimental research.

This study fills this research gap by offering a systematic investigation into the dynamic effects of brand crisis events relating both to product harm and CSI on consumer mindset metrics based on a unique dataset of 214 crisis events (both product failure and social misbehavior) in Germany across 12 industry sectors, 69 brands, and 5 years of weekly data. The authors aim to learn how strong the effects are, how persistent the damage is, and how long they endure. By using an ECM model, they apply a two-stage approach in order to estimate the short- and long-term impact of crisis events on brand attention and brand strength. Thereafter, the study analyzes drivers that explain why and when such events develop into severe brand crises. The principal measures used to analyze the impact and effects of the crises study include YouGov's Brand Index and advertising spend allocated before during, and after the crisis. YouGov's Brand Index score is particularly sensitive and revealing, as it tracks brand perception weekly.

The papers reveals several interesting findings. First, crisis effects are asymmetric. While brand attention increases, brand strength drops. Surprisingly, average brand damage is larger for corporate social misbehavior than for product failure. Furthermore, with respect to the duration of a crisis the damage may last up to 9 months. Finally, the effect aggravates if the firm denies responsibility, the event is a national event, and more media report on the news.

The findings provide important implications for managers. First and foremost, the results should warn against ignoring the risks of corporate socially irresponsible behavior. The study offers a clear message that such behavior may have a devastating effect on one of the most valuable corporate assets, the brand. There is an asymmetric focus on CSR and cause-related marketing activities in research and in practice. In the light of these findings, this partial attention is no longer warranted; the more so as the impact of CSR measures is rather modest.

The results are also valuable to managers because they help understand which events have the potential to develop into a deep and long crisis. The authors do not claim that every event of corporate social misconduct poses a threat to the brand. But there are conditions such as the type of crisis and media coverage that favor the occurrence of a severe crisis. The violation of environmental surroundings is very likely to turn into a major crisis. Similarly, the more media pick up on the crisis event the greater the chance that it becomes a severe crisis. Media coverage essentially has a double jeopardy effect as it also intensifies brand attention. Marketing management thus should closely follow the media coverage and maintain contact to journalists. The study also shows that denying the responsibility of a crisis in the beginning hurts the brand over time.

3.2 Paper II: Do Layoffs Hurt a Firm's Brand? – An Event Study With Consumer Mindset Metrics

In the aftermath of the financial crisis in 2012, every business day in the U.S. on average 4,000 people were laid off (U.S. Bureau of Labor Statistics 2013). News about downsizing is published almost every day and has become particularly prevalent during the last decade. These downsizing decisions, which often cost thousands of employees' jobs, are a regular means for companies to reduce costs (Chalos and Chen 2002). In the face of decreasing revenues, managers often intend to cut costs in order to improve efficiency.

However, the effectiveness of downsizing is controversially discussed. Short-term gains are possibly set off by long-term losses due to low employee motivation, low service levels, and decreasing skill bases (Datta el al. 2010). As a consequence, it is not clear whether, or to what extent, downsizing really enhances efficiency and firm performance.

In order to understand layoff effects researchers have primarily focused on the perspective of shareholders (financial performance) and employees (organizational performance). With respect to the threat layoff announcements bear towards consumers only scarce evidence exits (Habel and Klarmann 2015). A negative effect of downsizing announcements on consumer brand perceptions might oppose positive operational performance effects and lead to reduced sales in the long run. Therefore, brand effects could mediate the effect of layoff announcements on financial performance and provide a possible (at least partial) explanation why stock prices regularly plunge after such announcements.

This paper tries to fill this gap in literature by theoretically and empirically analyzing the impact of downsizing announcements on consumer brand ratings. The author investigates daily changes in consumer mindset metrics, namely brand attention, brand strength, and brand dispersion, immediately after layoff announcements. The customer mindset metrics relate to the two key components brand awareness and brand image of Keller's CBBE framework (1993) but also include brand dispersion to account for heterogeneity in brand perceptions. The empirical analysis is based on an extended event-study framework which is applied to a multi-national sample of 179 layoff announcements and 5 years of daily consumer mindset data across multiple sectors and firms.

As a result Paper II generates novel and surprising insights with respect to the effects of layoff announcements on consumer mindset metrics. Overall, the results indicate a significant but opposing effects on brand attention and brand strength. Layoff announcements have a significant positive effect on consumer brand attention but a significant negative effect with respect to brand strength. Furthermore, the significance effect in the abnormal changes in brand attention diminishes after about a week, whereas the negative effect on abnormal returns in brand strength does not. With respect to brand rating dispersion the analysis does not reveal any significant abnormal returns. Apparently, layoff announcements do not polarize enough between consumers to drive heterogeneity in brand evaluations. This implies that the overall effect of layoff announcements is especially driven by the negative effect in brand strength. With respect to drivers of the negative effect on brand strength the results reveal that on the one hand, the size of a layoff size amplifies the negative effect on consumer brand evaluations, on the other hand, a strong brand protects against a loss in brand strength.

Layoffs are usually undertaken by firms to increase operational efficiency but the intrinsic value is often questioned due to negative effects on e.g., employee satisfaction and service quality (De Meuse et al. 2004). The contributions of this study to the marketing literature are as follows: First, it enhances the understanding of the effect of layoff announcements on consumers and their brand perceptions. From a practitioner's perspective, this enables managers to incorporate brand effects into their consideration set to make better decisions. Second, the study provides an additional theoretical and empirical explanation of negative stock market reactions to layoff announcements, which supports the hypothesis that “hidden costs” may outweigh operational efficiency gains from downsizing measures. As a consequence, managers should think twice before deciding to downsize workforce significantly. Additionally, the results can also guide investors to better forecast stock market reactions to layoff announcements. Finally, by applying an event study approach relating actual downsizing events to daily information on consumer mindset metrics the empirical analysis comprises a new methodological approach for marketing researchers in order to study the effects of marketing actions on consumers. That is, the extended framework for event study analysis can serve as a starting point for future research. Marketers can thus use the framework accounting for the new data landscape in marketing.

3.3 Paper III: How Do Brands Generate Value For Investors? It’s From New Business And Competitive Distinctiveness

Top managers are increasingly demanding higher transparency on the financial impact of their investments. Building a sustainable competitive advantage and generating options for future growth is at the very core of marketing (e.g., Hunt and Morgan 1995). Therefore, it seems reasonable to assume that investors use marketing signals to update their beliefs about future growth and profits. While extant research at the marketing-finance interface demonstrates the value relevance of marketing (Srinivasan and Hanssens 2009), we know little about the manner in which value is generated and whether marketing impacts each of the growth-related value drivers and which of them most (Mizik 2014).

In this paper, the authors ask to what degree brand equity as an important market-based asset impacts these drivers of firm value that result from expected future growth. The study adopts the mental model of finance executives and investors and proposes an approach to quantify and estimate the dynamic contribution of marketing to firm value that arises from future profit growth. The authors build on a discounted cash flow valuation model of how investors determine the value of a company suggested by many financial studies (Copeland, Weston, and Shastri 2005). Based on this model, firm value is decomposed into the value of current earnings strength and the value of investments into future growth. The value of future growth is driven by four important factors: the return on invested capital, the cost of capital, the earnings growth rate, and the time period until the advantage in superior returns has eroded by competition (sustainability of excess return).

Based on a broad sample of 613 firms across a wide range of industries covering a period of 9 years from 2005 to 2013, the authors find that customer-based brand equity has a significant impact on three of the four value drivers. A mixed finding is detected with regard to the cost of capital. Specifically, for some firms a negative effect and for others a positive effect exists, which is in line with previous literature (Bharadwaj, Tuli, and Bonfrer 2011). Brand equity positively affects profitability, earnings growth, and the sustainability of excess returns. Furthermore, the results exhibit large differences in the responsiveness of the three financial value drivers to brand equity. Brand equity exerts its highest impact by improving the firm's ability to secure earnings growth and sustainable excess returns. However, the effects of marketing spending through brand equity on the four value drivers are considerably smaller in comparison to the substantial brand equity effects. This indicates that firms are, on average, operating closer to the optimum with respect to their advertising expenditures (Edeling and Fischer 2016).

The study extends prior research on the value relevance of brands by opening the black box and providing insights into the sources of value creation. Overall, the substantive insights into the magnitude of effects of advertising and CBBE on value drivers and ultimately firm value are the key contribution of the research project. The findings are valuable to both marketing practitioners and financial analysts. First, marketing managers benefit from these insights because they help them telling a compelling story about the value growth potential of marketing investments. The results show that brand value significantly impacts future firm value and growth expectations, however, managers need to find efficient ways for optimizing marketing spending in order to increase customer-based brand value. Second, the applied framework helps financial constituencies to think differently about their investment decisions. Investors gain a better understanding of how marketing impacts their key metrics. Since the research model conceptualizes and quantifies the routes of future cash flow generation, financial analysts may use the empirical estimates as a reference point in their valuation models.

References Synopsis

Ahluwalia, Rohini, Robert E. Burnkrant, and H. Rao Unnava (2000), "Consumer Response to Negative Publicity: The Moderating Role of Commitment," *Journal of Consumer Research*, 37 (2), 203-14.

Backhaus, Max and Marc Fischer (2016), "Brand Damage from Product-Harm and Corporate Social Irresponsibility – How Deep and How Long?," *MSI Working Paper Series*, forthcoming.

Bharadwaj, Sundar G., Kapil R. Tuli, and Andre Bonfrer (2001), "The Impact of Brand Quality on Shareholder Wealth", *Journal of Marketing*, 75 (5), 88-104.

Bazerman, Max H. and Anne Tenbrunsel (2011), "Ethical breakdowns," *Harvard Business Review*, 89 (4), 58–65.

Chalos, Peter and Charles J. P. Chen (2002), "Employee Downsizing Strategies: Market Reaction and Post announcement Financial Performance," *Journal of Business Finance & Accounting*, 29 (5-6), 847-870.

Copeland, Thomas E., John F. Weston, and Kuldeep Shastri (2005), *Financial Theory and Corporate Policy*. 4th ed. New Jersey: Pearson.

Cleeren, Kathleen, Harald J. Van Heerde, and Marnik G. Dekimpe (2013), "Rising from the Ashes: How Brands and Categories Can Overcome Product-harm Crises," *Journal of Marketing*, 77 (2), 58-77.

Datta, Deepak, K., James P. Guthrie, Dynah Basuil, and Alankrita Pandey (2010), "Causes and Effects of Employee Downsizing: A Review and Synthesis," *Journal of Management*, 36(1), 281-348.

Dawar, Niraj and Madan M. Pillutla (2000), "Impact of Product-Harm Crises on Brand Equity: The Moderating Role of Consumer Expectations," *Journal of Marketing Research*, 37 (2), 215-26.

De Meuse, Kenneth P., Thomas J. Bergmann, Paul A. Vanderheiden and Catherine E. Roraff (2004), "New Evidence Regarding Organizational Downsizing and a Firm's Financial Performance: A Long-term Analysis," *Journal of Managerial Issues*, 16(2), 155-177.

Edeling, Alexander and Marc Fischer (2016), "Marketing's Impact on Firm Value: Generalizations from a Meta-Analysis", *Journal of Marketing Research*, 53(4), 515-534.

Ghesquieres, Julien, Jeffrey Kotzem, Tim Nolan, Frank Plaschke, and Hady Farag (2016), "In a Tough Market, Investors Seek New Ways to Create Value," *BCG Perspectives*, May 2016.

Habel, Johannes and Martin Klarmann (2015), "Customer Reactions to Downsizing: When and How is Satisfaction Affected?" *Journal of the Academy of Marketing Science*, 43, 6, 768-789.

Hunt, Shelby D. and Robert M. Morgan (1995), "The Comparative Advantage Theory of Competition," *Journal of Marketing*, 59 (2), 1–15.

Kang, Charles, Frank Germann, and Rajdeep Grewal (2016), “Washing Away Your Sins? Corporate Social Responsibility, Corporate Social Irresponsibility, and Firm Performance.” *Journal of Marketing*, 80 (2), 59-79.

Katsikeas, Constantine S., Neil A. Morgan, Leonidas C. Leonidou, and G. Tomas M. Hult (2016), “Assessing Performance Outcomes in Marketing,” *Journal of Marketing*, 80 (2), 1-20.

Keller, Kevin L. (1993), “Conceptualizing, Measuring, Managing Customer-Based Brand Equity,” *Journal of Marketing*, 57 (1), 1–22.

Keller, Kevin L. (2008), *Strategic Brand Management*, 3rd ed. Englewood Cliffs, NJ: Prentice Hall.

Marketing Science Institute (2014), “*Research Priorities 2014-2016*”, Marketing Science Institute: Cambridge, MA, http://www.msi.org/uploads/files/MSI_RP14-16.pdf.

Mizik, Natalie (2014), “Assessing the Total Financial Performance Impact of Brand Equity with Limited Time-series Data,” *Journal of Marketing Research*, 51(6), 691-706.

Srinivasan, Shuba und Dominique M. Hanssens (2009), „Marketing and Firm Value: Metrics, Methods, Findings, and Future Directions,“ *Journal of Marketing Research*, 46 (3), 293–312.

U.S. Bureau of Labor Statistics (2013), BLS Reports September 2013: Extended Mass Layoffs in 2012, retrieved from http://www.bls.gov/mls/mlsreport1043.pdf on October, 3rd 2016.

Van Heerde, Harald J., Maarten J. Gijsenberg, Marnik G. Dekimpe, and Jan-Benedict E.M. Steenkamp (2013), “Price and Advertising Effectiveness over the Business Cycle,” *Journal of Marketing Research*, 50 (2), 177-93.

PAPER I: BRAND DAMAGE FROM PRODUCT HARM AND CORPORATE SOCIAL IRRESPONSIBILITY – HOW DEEP AND HOW LONG?

Authors: Max Backhaus and Marc Fischer

Abstract

Brand equity can suffer severely during brand crises. Managers understand the threat of a product failure to marketing assets and economic performance but seem to be less concerned about brand damage from corporate social misbehavior such as bribery. Academic literature is rich on product-harm crises but not much is known about the effects of corporate social irresponsibility events. Using an error correction model, we conduct a systematic investigation of the dynamic effects of brand crisis events on brand attention and brand strength based on a unique dataset of 214 crisis events (both product failure and social misbehavior) in Germany across 12 industry sectors, 69 brands, and 5 years of weekly data.

The crisis effects are asymmetric. While brand attention increases, brand strength drops. Surprisingly, average brand damage is larger for corporate social misbehavior than for product failure. The damage may last up to 9 months. The effect aggravates if the firm denies responsibility, the event is a national event, and more media report on the news. These findings help better forecast brand image drops during crises and give guidance to managers for appropriate reactions.

Keywords: Brand crises, brand attention, brand strength, product-harm, corporate social irresponsibility, error-correction model

1 Introduction

The brand constitutes one if not the most valuable intangible asset for many firms. These companies invest heavily in building their brands. A sudden and unexpected crisis event, however, poses a major threat to tediously established brand equity and previous investments reducing expected future economic performance of the firm (Cleeren, van Heerde, and Dekimpe 2013). The past is full of product failure examples. For example, Toyota's gas pedal crisis was broadly covered in the international press in 2009 and 2010. The company heavily suffered from its recalls of a total of about 8.5 million cars (Fan, Geddes, and Flory 2013).

Damages to the brand and firm performance from product/service failure are well known to managers. Their reaction often is fast and directed at eliminating the source of the problem via product recalls or product improvement since they understand there is a direct link between product failure and customer benefit. The academic literature has a long tradition in analyzing the causes and effects of product-harm crises.[2] Evidence is strong that such a crisis may indeed have severe detrimental effects on sales and marketing effectiveness (e.g., Dawar and Pillutla 2000; Gijsenberg, van Heerde, and Verhoef 2015; Van Heerde, Helsen, and Dekimpe 2007).

The perception that a firm has acted in a socially irresponsible way may also negatively affect the brand. In 2006, for example, Newsweek revealed spying activities at Hewlett Packard. The then chairwoman contracted private investigators to spy on board members and journalists to identify the source of an information leak. As a consequence of this scandal, she had to resign six months later. These kinds of corporate misbehavior tend to be increasingly reported in the media (Bonini, Court, and Marchi 2009). Indeed, our analysis of brand crises events covered in leading German media between 2008 and 2012 shows that only 50% of

[2] In this study, we consider product and service failure together under product-harm crisis, but acknowledge that there are important differences between product and service failures (Gijsenberg, van Heerde, and Verhoef 2015).

crisis events relate to product and service failure but the other 50%, in fact, root in corporate social misbehavior.

Although behavior-related crisis events happen as frequently as product-harm events they do not attract the same attention of management (Bazerman and Tenbrunsel 2011). Managers believe that it is bad publicity for the firm but without significant impact on customer behavior. Corporate misconduct is not as tangible as a product-harm crisis where the operational reliability or product safety is affected. This makes it difficult to infer whether and how consumers respond to the breach of rules and moral standards such as in the HP spying scandal. In addition, studies demonstrate a disconnection between stated socially responsible (desirable) behavior and actual behavior of customers. For example, consumers regularly express their concern about environmental pollution and declare they want to consume more of and pay more for ecologically sensitive products. But the market share for these products persists at a low level (e.g., Thompson and Arsel 2004). Hence, why should violations of corporate social responsibility (CSR) affect customer behavior?

Unfortunately, the CSR literature does not give much guidance on this question. It rather focuses on the meaning of and consequences of CSR than on corporate social *irresponsibility* (CSI) (Lange and Washburn 2012). However, consequences of CSR and CSI are likely not the same since losses tend to loom larger than gains (e.g., Gijsenberg, van Heerde, and Verhoef 2015). Hence, it is not appropriate to just extrapolate findings from extant CSR literature.

The vast majority of studies of brand crises consider product-harm events. But the transfer of findings from product-harm studies is limited since the nature of the crisis event and the affected parties usually are very different in corporate misbehavior events. Authors have only recently started to study the impact of observed CSI behavior (e.g., Flammer 2013, Kang, Germann, and Grewal 2016). These studies demonstrate the detrimental effects on bottom-line metrics but not on brand metrics. Most importantly, we are not aware of work that studies both observed product-harm and CSI events together. Many managers probably do not have a good feeling about the relative magnitude of these two classes of crisis events.

In this paper, we investigate the size and the duration of potential brand damage effects that result from both product-harm and CSR-related crisis events. We cover all such events that appeared in leading German media during the years 2008-2012 and relate them to representative weekly measures of brand attention and brand strength (the YouGov BrandIndex). This dataset comprises 214 crisis events of 69 involved brands from 12 industries.

Our analysis reveals important insights into the magnitude and dynamics of product-harm and CSI brand crises. Crises effects are asymmetric; while brand attention increases, brand strength drops. In addition and surprisingly, we find that the damage of brand strength due to CSI crises is deeper and cumulates to a larger total effect over time compared to product-harm crises.

We structure the remainder of this article as follows: First, we briefly review the related literature. We then develop our conceptual framework that helps explain differences across crisis events. This is followed by the description of our data collection, the research design, and the empirical model to estimate dynamic brand effects. We then present our estimation results and conclude with a discussion of the study's implications and limitations.

2 Related Literature

The prevalence and potential harmfulness of crises has attracted the attention of researchers for some time. Consistent with the great emphasis managers put on product/service failure events, the vast majority of studies deal with product-harm crises. But there is also a growing interest in CSI-related topics (e.g., Kang, Germann, and Grewal 2016;

Muller and Kräussl 2011). The crisis literature can be classified into two groups. The first group investigates the effects of hypothetical product-harm or CSI events in an experimental setting (e.g., Dawar and Pillutla 2000; Lei, Dawar, and Gürhan-Canli 2012). The majority of CSI research falls into this category (e.g., Ahluwalia, Burnkrant, and Unnava 2000; Pullig, Netemeyer, and Biwas 2006). A drawback of experimental research, however, is that insights are obtained under a hypothetical crisis setting. This limits the transfer of results to real, dynamic markets. Our study focuses on *real* product-harm and CSI events and their dynamic effects on brand attention and brand strength.

Table 1 positions our study relative to related prior research within this stream. Prior studies investigated the effects of product-harm crises on economic performance such as sales (e.g., Rhee and Haunschild 2006), sales response (e.g., Van Heerde, Helsen, and Dekimpe 2007), or shareholder value (e.g., Chen, Ganesan, and Liu 2009). Overall, there is unanimous evidence that a product-harm crisis may cause a severe drop in economic performance. Recent studies also demonstrate that product recalls and service failure events harm important intermediate marketing performance measures such as online word-of-mouth and perceived (service) quality (Borah and Tellis 2016; Gijsenberg, van Heerde, and Verhoef 2015).

Literature that studies the effects of CSI with observed company data in real markets is very limited (see Table 1). A recent study by Kang, Germann, and Grewal (2016) finds that firms benefit financially from CSR and that they use CSR strategically to offset past CSI. However, the penance mechanism does not appear to fully compensate for negative CSI effects suggesting the existence of asymmetric CSR and CSI effects. Hence, relative to product-harm crises, the effects of real CSI events appear to be underresearched. Our study contributes to this emerging research stream. It differs from prior studies in several ways and complements prior research on product-harm and CSI effects as Table 1 highlights.

Specifically, we investigate product-harm and CSI effects together, which enables us to draw conclusions about differences in the effect magnitudes. We focus on important brand-related mindset metrics: brand attention and brand strength. We further discriminate between types of corporate social misbehavior and study the moderating role of media coverage and immediate firm response to accusations in the media.

3 Conceptual Framework

3.1 Types of Brand Crisis Considered

We study four types of brand crises. Following the literature (e.g., Ahluwalia, Burnkrant, and Unnava 2000; Roehm and Tybout, 2006), we define the origin of a brand crisis as an unexpected, well-publicized event that threatens a brand's perceived ability to deliver expected benefits with potential negative effects for brand equity. The event is truly exogenous as it is a sudden, unexpected shock in the environment of the firm. This is a key feature of our identification strategy. To what extent this event eventually turns into a severe brand crisis can only be decided ex post. Consumers must become aware of it and change their brand perception. The drop of brand strength and possibly other performance measures reflects the magnitude of the crisis.

In this study, we consider two major groups of brand crises that root either in (1) product/service failures or (2) unethical firm behavior reflecting corporate social irresponsibility (see Table 2). We acknowledge that there may be other events that can cause a brand crisis, e.g., scandals associated with a brand testimonial or bad publicity about new products. If they are not related to product failure or unethical behavior, however, they are beyond the scope of our study.

Table 1: Streams of Research on Real Product-harm and CSI Effects

General research streams and key issues	Prior research	Product-harm effects studied?	CSI-harm effect studied?	Different types of CSI studied?	Effect on customer mindset studied?[1)]	Role of media studied?	Immediate firm response studied?[2)]	Dynamic effects studied?
Impact of product-harm crises on economic / firm performance metrics								
Specifically on...								
...on firm value (stock return)	• Chen, Ganesan and Liu (2009)	Yes	-	-	-	-	Yes	-
	• Thirumalai and Sinha (2011)	Yes	-	-	-	-	-	-
	• Hsu and Lawrence (2015)	Yes	-	-	-	-	-	-
...on sales	• Rhee and Haunschild (2006)	Yes	-	-	-	-	-	-
	• Cleeren, Dekimpe, and Helsen (2008)	Yes	-	-	-	-	-	Yes
	• Zhao, Zhao, and Helsen (2011)	Yes	-	-	-	-	-	Yes
	• Cleeren, van Heerde, and Dekimpe (2013)	Yes	-	-	-	Yes	-	-
...on sales response	• Van Heerde, Helsen, and Dekimpe (2007)	Yes	-	-	-	-	-	Yes
	• Rubel, Naik and Srinivasan (2011)	Yes	-	-	-	-	-	Yes
	• Liu and Shankar (2015)	Yes	-	-	Yes	Yes	-	Yes
...on reliability and firm's remedy decision	• Kalaignanam, Kushwaha, and Eilert (2013)	Yes	-	-	-	-	-	Yes
	• Liu, Liu, and Luo (2016)	Yes	-	-	-	-	Yes	-
Impact of product-harm/service crises on consumer metrics								
Specifically on...								
...on online WoM	• Borah and Tellis (2016)	Yes	-	-	Yes	Yes	-	Yes
...on perceived quality	• Gijsenberg, van Heerde, and Verhoef (2015)	Yes	-	-	Yes	-	-	Yes
Impact of CSI on economic / performance metrics								
	• Muller and Kräussl (2011)	-	Yes	-	-	-	-	-
	• Flammer (2013)	-	Yes	-	-	-	-	-
	• Kang, Germann, and Grewal (2016)	-	Yes	-	-	-	-	Yes
This study		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

[1)] We refer to studies that explicitly investigate the effect on customer mindset metrics. We do acknowledge, however, that several studies use mindset metrics as control or moderator variables in their design.
[2)] By immediate firm reaction we refer to how the firm responds to the accusations in the media. The immediate response encompasses 3 options: deny responsibility, accept responsibility, or do not respond. We note that prior studies also considered firms' reactive behavior in terms of advertising or CSR activities.

Product-harm crisis. Product-harm crises are well described in the literature. Underlying causes relate to deviations from product quality or inadequate service that lead to product defect, production stop, or product recall (Dawar and Pillutla 2000).

Table 2: Description of Crisis Types

	Product-harm crisis	**Corporate Social Irresponsibility (CSI) crisis**		
		Violation of fair operating practices	Violation of human rights / working conditions	Environmental scandal
Definition	Deviations from product quality or inadequate service	Management misconduct relating to corporate governance or social norms and societal rules	Violation of compliance with human rights and conditions of employment	Violation and endangerment of environmental surroundings
Event types	• Production stop • Product defect • Product recall • Service failure	• Corruption - Bribery - Breach of trust - Money laundering - Tax disputes - Investment controversy • Transparency violations • Consumer fraud with regard to - Sales practices - Pricing policies	• Human rights violations • Violations of employee relations with respect to - Benefits and wages - Local working conditions - Discrimination - Foreign labor issues - Diversity standards	• Violation and endangerment of animals / wildlife • Violation and endangerment of nature
Example	Toyota gas pedal/floor mat crisis	Deutsche Bank tax fraud crisis	KIK employee scandal	BP Deepwater Horizon oil spill
	Over 6 million recalled vehicles after reports showed that several vehicles experienced unintended acceleration Date: 01/25/2010	Deutsche Bank admitted criminal wrongdoing and agreed to pay $ 554 million over fraudulent tax shelters that generated $ 29 billion in tax losses. Date: 12/20/2010	Media reported that KIK systematically spies on employees, pays below minimum wages, and exploits suppliers Date: 09/07/2010	Discharge of 4.9 million barrels of oil causing extensive damage to marine and wildlife habitats and fishing and tourism industries Date: 04/20/2010
KLD [1] issue areas	Product[2]	Community Corporate Governance	Diversity Employee relations Human rights	Environment

[1] Kinder, Lyndenberg, and Domini (KLD) provides a Social Ratings Database that tracks firm's strengths and concerns in seven issue areas over the year. It has been widely used in academic research.
[2] This dimension includes product safety concerns but also marketing/contracting and antitrust concerns, which are rather characteristics of a CSI and less of a product-harm crisis.

CSI crisis. A CSI crisis does not originate from product failure but from ethical, social, or environmental issues attributed to the brand or the firm (Lange and Washburn 2012). These incidents question the brand's ability to deliver symbolic and psychological benefits. We distinguish three different categories of socially irresponsible firm behavior: violations of fair operating practices, violations of human rights or working conditions, and environmental scandals. Table 1 describes the scope of these crisis types and provides examples from our later empirical dataset. Our crisis types fully span the issue areas that are covered by KLD's Social Ratings Database, which has been used in prior studies (e.g., Kang, Germann, and Grewal 2016).

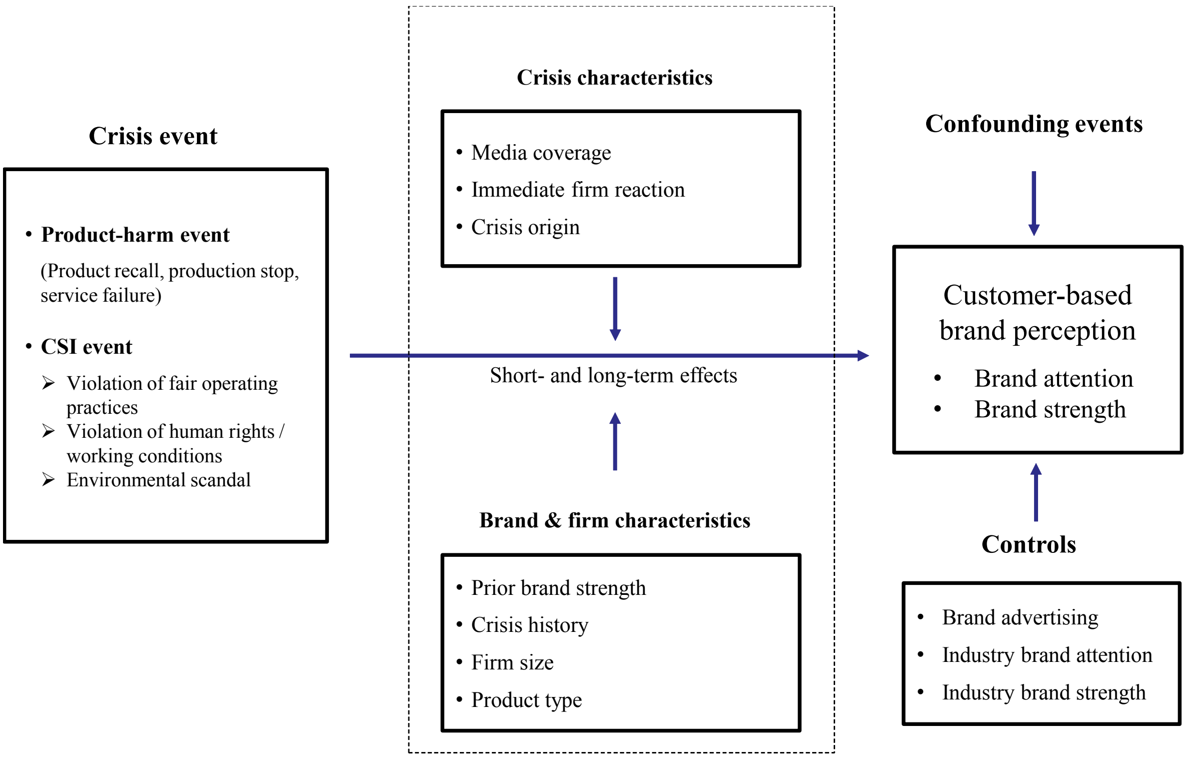
We do not exclude the possibility that a product failure may result from unethical behavior. A recent example is the massive product recall of Volkswagen cars because of manipulated software to hide their pollution level. If these different kinds of information are delivered to the public from the very beginning the event is actually a mixture of a product-harm and CSI crisis. In the vast majority of cases, however, the media initially report solely on the product-harm event such as a recall or defect. If at all, unethical behavior leading to the product issues is reported only later. We account for ambiguous crisis type assignments in our empirical analysis.

3.2 **Focal Performance Metrics**

The brand represents a major asset for many firms. Monitoring and tracking intermediate customer mindset metrics such as brand attention and brand strength is crucial to these firms. Conceptually, brand metrics are informative and predictive for economic performance because they are logically a precursor of customer acquisition and retention that drive sales and profits (e.g., Rust, Zeithaml, and Lemon 2004; Stahl et al. 2012). Recent empirical studies indeed demonstrate that there is a strong link between mind-set metrics and (future) transactions (e.g., Hanssens et al. 2014; Stahl et al. 2012).

This study focuses on brand attention and brand strength as brand performance metrics. Brand attention measures the level of awareness due to the amount of available positive or negative information about the brand. Brand strength is a composite measure that covers several image and performance dimensions of a brand as perceived by the customer. Conceptually, both brand awareness and brand image are the constituent parts of Keller's (1993) model of customer-based brand equity. We provide more measurement details on these metrics subsequently.

Figure 1: Conceptual Framework



3.3 Conceptual Model

Figure 1 shows the conceptual model that we use to explain and measure the crisis effect on the brand. Our basic premise is that the crisis event has a negative impact on brand strength but a positive effect on brand attention. According to Berger, Sorensen, and Rasmussen (2010), negative news coverage is also publicity that boosts brand attention, which can even increase sales. Whether negative publicity increases or decreases sales depends on existing brand awareness and accessibility. For well-known brands, the effect should be negative as shown in several studies (e.g., Basuroy, Chatterjee, and Ravid 2003). A rather unknown brand, however, could benefit from the (negative) media hype, particularly if attention and publicity valence become dissociated in memory (Berger, Sorensen, and Rasmussen 2010).

The changes in brand attention and strength can be immediate and/or evolve over time. The crisis event may even lead to a persistent brand effects.

Control variables. In an actual market situation, we need to control for other influences that might impact the brand metrics. First of all, we control for other events that may confound the crisis effect. Such confounding events are new product introductions, quarterly earnings announcements, etc. In addition, we consider three control variables: brand advertising expenditures, industry brand attention, and industry brand strength. Advertising expenditures are a major driver of the brand (Keller 1993). Hence, we expect this variable to positively influence brand attention and strength. Industry brand attention and strength are important control variables. They incorporate influences within an industry that affect all brands together and drive attention and strength. For example, the overall image of banks heavily suffered in the aftermath of the great financial crisis. Thus, we expect a positive relationship between industry brand attention and strength, respectively, and the focal brand's attention and strength, respectively.

Moderators of the brand effect: crisis characteristics. Every crisis is different. These differences moderate the impact of the crisis event on brand perception. We consider three crisis characteristics that have also been discussed in prior research (e.g., Liu and Shankar 2015), namely media coverage, immediate firm reaction, and crisis origin.

Media coverage. In the event of a brand crisis, the role of the mass media in the construction of negative publicity is crucial (Liu and Shankar 2015). Negative news from media publications serve as an external source of information and, hence, are regarded as more trustworthy by consumers than information directly from the owner of the brand. The more media report about the crisis event, the larger is the chance that consumers will be exposed to the news. Thus, we expect higher media coverage to increase positive effect of a crisis event on brand attention and the negative effect on brand strength.

Immediate firm reaction. The immediate reaction of the firm on the crisis news probably plays another important role. There is no common typology of firm reaction in a crisis. We adopt a straightforward approach that covers the continuum of possible reactions. Specifically, we follow Dutta and Pullig (2011) and consider three immediate firm reactions: deny responsibility, accept responsibility, and no reaction. Firms may deny any responsibility for the crisis and blame other firms, e.g., their supplier. At the opposite, they might take the blame for the crisis, actively apologize and try to rebuild trust in the company (accommodating strategy). Finally, as a start, firms often do nothing, i.e. they do not respond to the negative publicity at all.

Intuitively, there may be good reasons to accept responsibility and expect this to be the most successful strategy. However, there are also arguments that the effectiveness of any response depends on various factors including consumers' expectations of the firm response (Dawar and Pillutla 2000), commitment to the brand (Ahluwalia, Burnkrant, and Unnava 2000), and the nature of the crisis (Lange and Washburn 2012). Chen, Ganesan, and Liu (2009), for example, find that an accommodating strategy amplifies the negative effect on the firm value compared to a passive strategy. Hence, we do not formulate a-priori expectations about the influence of this moderator variable but leave it as an interesting empirical issue.

Crisis origin. The origin of a crisis may lie in the country where the observer lives or outside this country. Child labor accusations of international companies operating in Asia, for example, are discussed in the US and German press, but the event happens far away from these consumers' home country. A crisis occurring on the doorstep of the consumer is probably more relevant and personally threatening. In terms of self-preservation, the observer processes the effect to be more undesirable that should be avoided (Lange and Washburn 2012). Therefore, we expect that a crisis originating in the home country to have a stronger negative effect on brand strength. We have no expectation for the direction of influence on the brand attention effect.

Moderators of the brand effect: brand & firm characteristics. In addition to the crisis event itself, characteristics of the brand and the firm may play a moderating role. We consider four moderators: prior brand strength, crisis history, firm size, and product type.

Prior brand strength. Following Berger, Sorensen, and Rasmussen (2010), we expect a negative moderation effect of prior brand strength with respect to brand attention. They argue that the gain in awareness due to negative publicity is lower the more known or stronger a brand is. People exposed to new information about their preferred brand tend to perceive positive news to be more insightful than negative information, as opposed to non-customers who tend to put more weight on negative news (Ahluwalia 2002). Put differently, consumers process negative crisis information about less known and less preferred brands as primary information. In contrast, they discount negative information for their preferred brands to avoid inconsistency with their brand knowledge. Product-harm research indeed found that product trial probabilities for stronger brands suffer less from the crisis (Cleeren, Dekimpe, and Helsen 2008). Hence, we expect brand strength to serve as a protection against the negative effect of a crisis event.

Crisis history. Crisis history indicates whether the crisis is a one-time event or part of a pattern of similar crises. A history of crises suggests an organization has an ongoing problem that needs to be addressed. The observer learns that the firm has a tendency to act in this way over time, which increases the evidence for causal culpability (Zautra et al. 2005). On the contrary, companies without a history of prior brand crises suffer less since consumers are more willing to forgive a one-time mistake (Liu and Shankar 2015). Consequently, we expect crisis history to amplify the negative effect on brand strength. The effect on the attention effect, however, is not clear.

Firm size. When assessing the firm's responsibility in the event, observers also consider the congruence between size and effect (Lange and Washburn 2012). It is plausible that a large firm causes a large effect, but less so for a smaller firm. Therefore firm size should amplify the negative effect on brand strength. On the other hand, large firms are also established firms that have grown in reputation over time. Similarly to the brand strength effect, this reputation might act as a shield against brand damage effects leaving the direction of the effect as an empirical issue. Smaller firms are likely to have smaller brands that are less known. Following again the line of arguing of Berger, Sorensen, and Rasmussen (2010), we expect a negative influence of firm size on the attention effect of crises.

Product type. The magnitude of the brand effects might also depend on the product type that differs in terms of perceived risk, product involvement, or purchase frequency (Nelson 1970). We distinguish four types: non-durables, durables, services, and retail. Since it is difficult to draw well-founded inferences about the role of product type characteristics we do not formulate a priori expectations.

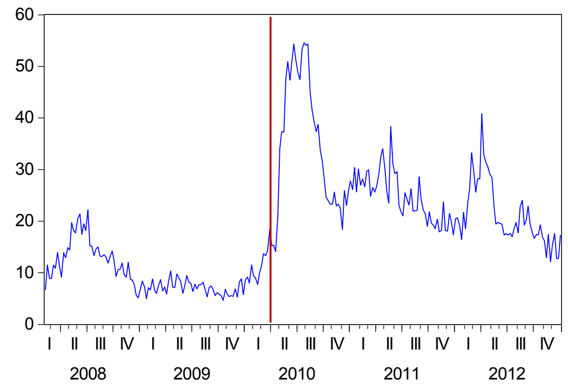
3.4 **Initial Evidence**

Figure 2 shows the time series of brand attention and brand strength for two exemplary brands that faced major crisis events within our observation period. The left image portrays BP. In the spring of 2010, an oil rig exploded and sank causing a massive pollution of the maritime environment (environmental scandal).

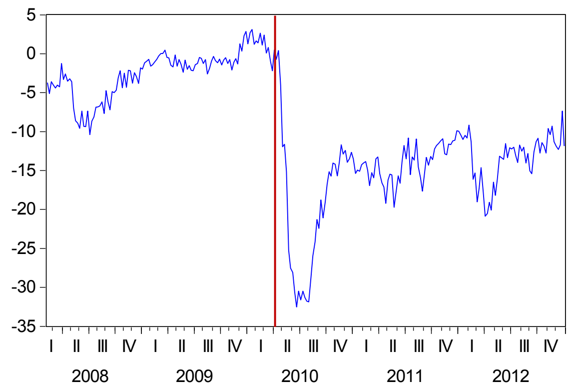
Figure 2: Exemplary Time-Series for Brand Attention and Brand Strength

BP
(Global oil and gas company)

Brand attention



Brand strength

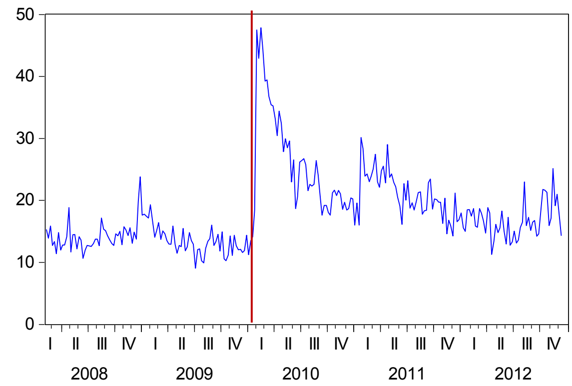


Crisis event: Environmental scandal

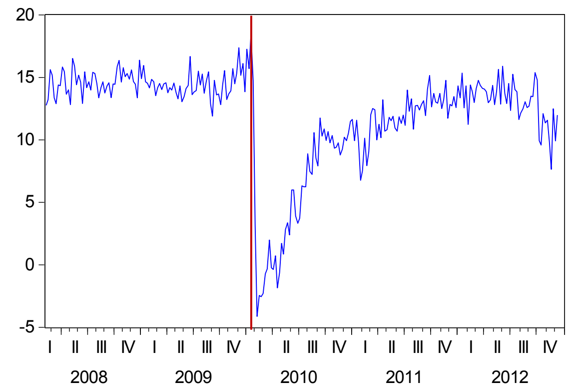
Explosion and sinking of oil rig caused major environmental catastrophe
(Date: April 2010)

Toyota
(Global automobile manufacturer)

Brand attention



Brand strength



Crisis event: Product-harm crisis

Toyota recalled millions of vehicles due to unintended acceleration problems
(Date: January 2010)

In the same year, Toyota faced its largest product recall in history and had to call back millions of vehicles due to an unintended acceleration problem (product-harm crisis). The right image shows Toyota's brand evolution in terms of attention and strength. In both graphs, the occurrence of the crises events coincides with a heavy spike in the brand time-series. Brand attention jumps to a new maximum height and brand strength drops to a minimum level. This behavior suggests that a crisis event may have a substantial impact on both brand metrics. We acknowledge that there are several other spikes in the time-series, which may have been caused by other events including additional crisis events.

4 Data and Method

The crisis event is a temporary, exogenous shock, but not a permanent change. The resulting brand crisis is endogenous. We define its depth and length by the ex-post change in brand attention and brand strength that is due to the event. Our objective is to estimate and explain this effect (see Figure 1 again). To achieve this goal we analyze brand time-series data. Specifically, we use five years of weekly data from Germany in the period 2008 to 2012.

4.1 Brand Measures

We have access to a unique database that offers a nationwide measurement of brand perception at the weekly level. The YouGov group, a global market research company specializing in online panels, collects this data. Their online panel consists of 3 million panelists across 11 countries including 170,000 panelists in Germany. Here, YouGov monitors the 600 largest brands across all relevant B2C sectors on a daily basis. Brand attention represents the number of respondents who are aware of either negative or positive news about a brand. Brand strength is measured along six dimensions, which are aggregated to the YouGov BrandIndex. These dimensions are perceptions of: brand quality, brand value, brand satisfaction, brand recommendation, brand identification, and brand overall impression.[3] Details on the exact items and the collection of data are provided in the Appendix.

In the Appendix, we also provide details on construct validation. Specifically, we show that the six brand dimensions are indeed reflections of the same underlying brand strength construct. Brand strength, however, is distinct from brand attention (correlation = .17, $p < .01$) according to the Fornell/Larcker test. The confirmatory factor analysis model passes all common thresholds of model fit and tests on construct validity and item reliability (see Appendix).

The big advantage of the BrandIndex over other brand strength measures such as Young&Rubicam's BAV (e.g., Stahl et al. 2012) is that it is available at the disaggregate (weekly) level. This allows for detecting changes in brand perception triggered by single events such as press reports on firm misbehavior.

At the aggregate brand level, brand attention and brand strength scores fall within the range of -100 to +100. For brand strength, as an example, the extremes are only realized if all respondents agree in their negative or positive perception of the brand relative to its competitors. The weekly brand ratings are based on a large sample of at least 700 responses. This helps reducing the sampling error. The weekly periodicity also aligns well with the measurement of the crisis event. Note that the first media reports do not always appear on the same day. In addition, not all consumers receive and process news immediately but with a time lag over the next few days.

4.2 Brand Crisis Events

Using the Lexis Nexis database, we identified brand crisis events through a comprehensive media search in the 15 leading online and offline media sources in Germany.[4]

[3] In 2013, YouGov expanded the number of items in the survey, among them questions on purchase consideration and intent. Our observation period ends before this change.

For each crisis type (see Table 2 again), we generated a pre-tested list of keywords and systematically searched for the keywords in connection with the specific brand (see the Appendix for details). We require that a "well-publicized" event must have been reported by at least 3 media to ensure it attains a sufficient reach within the German population. We test this assumption (see the Appendix).

We identified a total of 373 brand crisis events within the period of 2008 to 2012. 113 cases had to be excluded because media coverage was below 3 media sources. We had to exclude another 12 cases due to confounding events such as overlapping crisis events, new product introductions, etc. Finally, 34 additional cases are eliminated from the sample because of missing information on control variables such as advertising expenditures. Thus, our final sample size covers 214 crisis events (see the Appendix for the list of events) across 12 industries, 69 brands (ca. 12% of brands covered by YouGov), and 5 years of weekly data. We define the week, in which the first report was published on the event, as the event date.

Three coders (one co-author) read every report related to a specific crisis event. Based on the conceptual meaning of the four crisis types (see Table 2 again), they assigned each event to one type. They also paid attention to situations where an event could be both classified as a product-harm and a CSI event. This applies to only a small number of 27 crisis events (12.6%). If there was disagreement on the assignment of a crisis type it was solved by discussion.

4.3 Control and Moderator Variables

We obtain data on control and moderator variables from various data sources. Ebiquity provides weekly brand advertising expenditures across several channels. Industry brand attention and strength are the averages (excluding the focal brand) for the industry sector.

---

[4] For newspapers and online news portals not included in Lexis Nexis, we performed individual searches in the respective data archive.

Media coverage is based on the press research of brand crisis events and counts the number of media sources (Cleeren, Van Heerde, and Dekimpe 2013). Based on the information in the media articles, the three coders also determined the immediate firm reaction according to the three possible strategies. Coding agreement is greater than 95%. Note that a firm's reaction may change over the course of a crisis. Our measure does not account for such change because we focus on the crisis event and the immediate reaction of firms. There was virtually no disagreement regarding the origin of a crisis (Germany versus foreign country).

Prior brand strength is the focal brand's average BrandIndex in the 12 weeks prior to the crisis event. Crisis history measures the number of remembered crisis events for the focal brand. We apply a time weight to the accumulation to account for the process of forgetting. This weighting also alleviates the censoring issue that is associated with this variable. But we still note that this measure is not perfect since we do not observe the complete crisis history of a brand. Firm size is based on the number of employees and is obtained from Compustat. Product type follows the common classification of goods as durables, non-durables, services, and retail. Table 3 informs about the details of measurement for each variable.

Table 3 provides descriptive information about the sample. Panel A informs about the variables that enter our subsequent model to measure the brand effects. Brand attention, brand strength, and advertising expenditures show strong variation. SD is larger than the mean for two variables. This also applies to the distribution of crisis types. 49% of the events are product-harm events, 51% are CSI events. This distribution underlines the relevance of potential CSI crises. Most of the CSI crisis events were violations of fair operating practices (27%), followed by violations of human rights and working conditions (21%) and environmental scandals (4%).

Table 3: Variable Definitions and Summary Descriptives

Variable	*Description*	*Source*	*N*	*M*	*SD*
Panel A: Time-series data for estimating ECM (see Equation 3)					
Focal variables					
Brand attention	Index from -100 to +100, relating to the question whether respondents have heard anything positive or negative about the brand within the last 2 weeks	YouGov	17,043	23.10	9.77
Brand strength	Index from -100 to +100 aggregated across 6 brand perception dimensions: brand quality, brand value, brand satisfaction, brand recommendation, brand identification, brand overall impression	YouGov	17,043	12.60	17.09
Crisis types [a]					
Product-harm crisis	Dummy for occurrence of crisis event in week t	Press research	105	49%	50%
FOP violation	Dummy for occurrence of crisis event in week t	Press research	57	27%	44%
HR / WC violation	Dummy for occurrence of crisis event in week t	Press research	44	21%	40%
Environmental scandal	Dummy for occurrence of crisis event in week t	Press research	8	4%	19%
Controls		*Total*	*214*		
Ad expenditures	Weekly advertising expenditures in 1,000 € across major media channels (television, radio, print, outdoor, online)	Ebiquity	17,163	1,139	1,630
Industry brand attention	Weekly average brand attention across all brands in focal brand's industry (excluding the focal brand)	YouGov	17,664	9.68	3.20
Industry brand strength	Weekly average brand strength across all brands in focal brand's industry (excluding the focal brand)	YouGov	17,664	5.76	4.51
Panel B: Cross-sectional data for estimating moderator effects (see Equations 4 and 5)					
Media coverage	Number of newspapers and online news portals that reported on the crisis event	Press research	214	6.50	3.0
Immediate firm reaction [a]	Dummy for immediate firm reaction after the event was published	Press research			
	No reaction: passive to no reaction (=1) if not (=0)		98	46%	50%
	Deny: deny responsibility (=1) if not (=0)		49	23%	42%
	Accept: apologize/accept responsibility (=1) if not (=0)		66	31%	46%
Crisis origin[a]	Dummy variable indicating whether geographic origin of crisis was international (=0) or national (=1)	Press research	153	71%	46%
Product type [a]	Dummy variable for product type of the business	MSCI GICS			
	Durables (=1) if not (=0)		12	6%	23%
	Non-durables (=1) if not (=0)		107	50%	50%
	Retail (=1) if not (=0)		41	19%	39%
	Services (=1) if not (=0)		54	25%	44%
Prior brand strength	3-month average of BrandIndex prior to focal crisis event	YouGov	214	14.41	18.53
Crisis history	Remembered (time-discounted) number of crisis events since 2008 until focal crisis event	Press research	214	1.4	1.5
Firm size	Number of employees (in 1,000)	Compustat	69	123.4	118.3

[a] For these variables, we report the percentage of observations having the value of 1.

Notes: We report the statistics for the dependent variable before the log transformation. FOP = Fair operating practices, HR = Human rights, WC = working conditions, GICS = Global Industry Classification Standard.

4.4 Descriptive Statistics

Panel B of Table 3 shows the descriptive statistics for our moderator variables. The average crisis event is covered by 6.5 media outlets out of 15. The vast majority of these events originate in Germany (71%). Unsurprisingly, media are biased towards reporting about national events. Half of the 69 covered brands had two or less crisis events during our observation period. The maximum is 15 events (Toyota). The most often immediate firm reaction was no reaction (46%), followed by acceptance of responsibility (31%) and denial of responsibility (23%). To summarize, the variation in the data is strong supporting the proper identification of effects.

Figure 3: Empirical Strategy

1. Identify product-harm and CSI events	• Comprehensive press search for relevant articles in Germany in 2008-2012 • Exclude crisis events with confounding events
2. Test for model free evidence	• Conduct difference-in-difference tests with controlled, quasi-experimental design
3. Test for conditions of persistent effects	• Test for unit root in brand perception of focal brand and industry, brand advertising expenditures, and consumer interest *Individual tests:* Augmented Dickey-Fuller Test, Phillips-Peron test, Kwiatkowski–Phillips–Schmidt–Shin test • Test for cointegration for evolving variables using residual-based Pedroni and Kao cointegration tests
4. If no evidence for persistent effects provided, estimate immediate and cumulative brand crisis effect	• Estimate error-correction model (ECM) for each brand time-series • Obtain immediate and cumulative effects for each brand crisis event from parameter estimates
5. Estimate the impact of moderator variables on immediate and cumulative crisis effects	• Regress estimated immediate and cumulative brand-crisis-event effects on set of moderator variables

4.5 **Method**

Empirical Strategy. Figure 3 outlines our empirical strategy. We proceed in five steps. We already reported on the first step that involved the identification of all potential product-harm and CSI events that became public in Germany during our observation period. After eliminating the confounded events, we test for model-free evidence. Specifically, we use a quasi-experimental difference-in-differences test format. A limitation to this design is that we can only detect contemporaneous effects but no dynamic effects. We therefore continue with time-series modeling and start with testing for the time-series properties in step 3. In particular, we check for unit roots in all relevant time-series variables (brand attention, brand strength, advertising expenditures). The existence of a unit root is a prerequisite to establish persistent crisis effects. Provided we do not find evidence for persistency, we estimate the immediate and cumulative effects of the event shock on the focal brand's attention and strength in the third step. We retain the effect estimates for all brand crisis events and regress them on the set of moderator variables in the final step.

Identification. Our identification strategy rests on the assumption that we exploit a large number of crisis events, which vary across types of product-harm and CSI events (see Table 3 again). They represent a random shock to the observed brand time-series. A crisis event can be considered truly exogenous because the large population of consumers does not have knowledge about the crisis event before it is reported in the media. The endogenous brand evaluations are obtained before and after the event in a representative customer survey. We also verify our exogeneity assumption in a "Granger-like causality test (see the Appendix).

Our research design thus follows the idea of the established event study methodology (McWilliams and Siegel 1997). For example, Flammer (2013) searched for articles that report on eco-friendly and eco-harmful behavior to study the effect of the publication date on stock return. Our approach is very similar since we also search for media reports on crisis events and study the effect of that event date on brand attention and brand strength. To rule out alternative explanations we carefully check for confounding events around the time of the crisis event.

We also have data on the focal brand variables available for a group of up to 25 competitive brands. This set establishes a control group. We therefore have a design that constitutes a controlled, repeated quasi-experiment. We acknowledge, however, that it is not a rigorous, fully randomized experiment since there is no control about which brands undergo a crisis – a limitation that we share with all prior research on actual brand crises.

Sample selection. Another aspect of our study design refers to the selection of brands and crisis events. Note that two conditions must be met for a brand to be sampled. First, a product/service failure or unethical firm behavior must happen, which may or may not be uncovered. Second, media must report on the event. We believe the first condition does not create a selection issue. Every firm is likely to run into a product or ethical behavior issue in the long run.

Our observation period of 5 years should be long enough to observe a representative sample of these events. In fact, we can show that the brands in our crisis sample do not significantly differ along variables such as brand strength, advertising expenditures, and industry membership from the YouGov brand universe (see the Appendix). The second condition, however, is likely to follow a selection process. Editorial journalists presumably choose stories in a strategic way. For example, they might prefer reporting on larger companies and better-known brands. However, our findings are not biased if only those larger brands are selected in our sample. This is because an unselected but unreported crisis event of a small brand does not affect consumers' brand perception.

5 Modeling and Estimation Issues

5.1 Measuring the Crisis Effect on Brand Attention and Brand Strength

The YouGov brand metrics are ratio-scaled variables that run from -100 to +100 (for details see the Appendix). We focus on brand strength in the following. Brand attention is modeled in the same fashion using the same set of predictor and moderator variables. We model the evolution of the BrandIndex as follows (Hanssens, Parsons, and Schultz 2001, 110):

$$BI_{it} = MIN + (MAX - MIN)\frac{1}{1+e^{-f(\mathrm{X}_{it})}} \ , \tag{1}$$

where BI_{it} measures the BrandIndex (= brand strength) of brand i in week t and $f(\mathbf{X}_{it})$ is a function that captures the influence of crisis events and controls, summarized in vector **X**, on the BrandIndex. Equation (1) satisfies the range restriction of our focal variable, with MIN = -100 and MAX = +100. As a result, the relation between BI and the predictor variables is nonlinear and follows an S-shape. Taking the log and rearranging terms leads to a model that is linear in parameters:

$$\widetilde{BI_{it}} = \ln\left(\frac{BI_{it} - MIN}{MAX - BI_{it}}\right) = f\left(\mathrm{X}_{it}\right). \tag{2}$$

Note that our log-transformed dependent variable is no longer range-restricted and thus satisfies the assumption of a normally distributed error term. Assuming the time-series are stationary or at least co-integrated (which we test for), we adopt a parsimonious error correction model (ECM) to estimate the immediate and cumulative effects (e.g., Pauwels, Srinivasan, and Franses 2007, Van Heerde et al. 2013). Specifically,

$$\begin{aligned}\Delta\widetilde{\mathrm{BI}}_{\mathrm{it}} = {} & \alpha^{\mathrm{Imm}}_{0\mathrm{i,Strength}} + \sum\nolimits_{\mathrm{k}} \beta^{\mathrm{Imm}}_{\mathrm{ik,Strength}} \Delta \mathrm{C}_{\mathrm{ikt}} + \lambda^{\mathrm{Imm}}_{1\mathrm{i,Strength}} \Delta\mathrm{ADV}_{\mathrm{it}} + \lambda^{\mathrm{Imm}}_{2\mathrm{i,Strength}} \Delta\mathrm{IBI}_{\mathrm{it}} \\ & + \gamma_{\mathrm{i,Strength}} \begin{bmatrix} \widetilde{\mathrm{BI}}_{\mathrm{it}-1} - \sum\nolimits_{\mathrm{k}} \beta^{\mathrm{Cum}}_{\mathrm{ik,Strength}} \mathrm{C}_{\mathrm{ikt}-1} - \lambda^{\mathrm{Cum}}_{1\mathrm{i,Strength}} \mathrm{ADV}_{\mathrm{it}-1} - \lambda^{\mathrm{Cum}}_{2\mathrm{i,Strength}} \mathrm{IBI}_{\mathrm{it}-1} \\ -\alpha^{\mathrm{Cum}}_{1\mathrm{i,Strength}} \mathrm{Trend} \end{bmatrix} + \upsilon_{\mathrm{it,Strength}} \end{aligned} \tag{3}$$

where Δ is the first difference operator: $\Delta\widetilde{BI}_{it} = \widetilde{BI}_{it} - \widetilde{BI}_{it-1}$. C_{ikt} is a dummy variable that measures the occurrence of the kth crisis *event* for brand i in our observation period, with $k \in K_i$. Consistent with the event-study methodology (McWilliams and Siegel 1997), we treat the week of first publication of a crisis event as an external shock that potentially impacts brand perceptions in the market. The estimated event's impact on brand strength is our measure of the magnitude and duration of a crisis. Hence, the crisis is endogenously defined in our framework, i.e. derived from estimated parameters. Empirically, we observe that the vast majority of events (>80%) are reported in the first and second week. Results are robust to a two-week dummy specification. If media reports for the same brand occur at a later point in time (for example, Toyota announced multiple recalls over months in 2009 and 2010 due to several reasons; Fan, Geddes, and Flory 2013), we treat them as new crisis events.

ADV denotes advertising expenditures and IBI denotes the focal brand's average industry brand strength value. Trend measures the time period. Following van Heerde et al. (2013), it runs from -1 in the first observation to +1 in the last.

The ECM is a useful transformation of a VARX model in an error correction format. Estimation is not plagued by collinearity among current und lagged variables and model parameters are easy to interpret. The α-parameters (α^{Imm}, α^{Cum}) are trend parameters, the β-parameters (β^{Imm}, β^{Cum}) measure the immediate and cumulative effect of the crisis events, the λ-parameters (λ^{Imm}, λ^{Cum}) refer to the influence of the control variables, and γ is an adjustment parameter that measures the speed of adjustment to the (long-term) equilibrium. This parameter is especially relevant for measuring the duration of a crisis. In addition, we obtain the immediate (superscript *Imm*) and the cumulative (superscript *Cum*) effects of a crisis and the control variables. Cumulative effects measure the immediate and future changes in brand ratings due to the temporary shock of the crisis event. We test for persistence before estimating Equation (3).

5.2 **Simultaneity Issues**

Research on product-harm crises (e.g., Rubel, Naik, and Srinivasan 2011) has shown that firms change their advertising expenditures in anticipation of changes in economic performance after the occurrence of a crisis event. It can also be argued that if industry brand perception affects the perception of the focal brand there might exist spillover effects from the focal brand to other brands in the industry, especially in a crisis situation (Lei, Dawar, and Lemmink 2008). To address these potential simultaneity issues and reduce the danger of biased estimates we treat the change in advertising and in industry brand strength as endogenous and employ an instrumental variables approach.

We follow recent ECM studies (e.g.; Gijsenberg 2014; Van Heerde et al. 2013) and use both the first-differenced and lagged advertising expenditures in industries of other product types to identify ΔADV_{it}. Specifically, we use durable goods, non-durable goods, services and retail as classes (excluding the focal brand's type). Advertising expenditures changes in other industries are likely due to the same underlying cost structures (Van Heerde et al. 2013), but these structures should not be related to shocks in brand attention/strength in the focal brand's industry.

We adopt a similar strategy to instrument ΔIBI_{it}. Again, we use the change and lagged values of the average brand strength of other product types. The idea is that changes in average brand strength of other industries arise from the same source such as a common trend or correlations among advertising expenditures due to the same underlying cost structures. We follow the same procedure for industry brand attention.

Since we have more (outside) instruments than possibly endogenous predictors the model is overidentified. All other predictors including lagged variables are predetermined and serve as their own instruments. We formally assess both the strength (multivariate F-test) and the validity of the exogeneity assumption with respect to our instruments (Hausman-

Sargan test) (see Greene 2012, pp. 249-251). The F-test supports the strength of the instruments (p-value of F-test < .05). Additionally, we cannot reject the exogeneity assumption (lowest p-value of Sargan test > .14).

5.3 **Heterogeneity**

The effects of crisis events on consumers are likely to vary across brands. We estimate the model for each brand time-series and obtain brand-specific estimates for the immediate and cumulative effects. We calculate the estimates of the cumulative parameters of interest from the initial estimates of the different products of parameters (e.g., $\gamma_i \lambda_{1i}^{Cum}$) and derive the associated standard errors with the Delta method (Greene 2012, p. 330-331).5 We summarize effect sizes of our parameters of interest by Rosenthal's method of added Zs (Rosenthal 1991). The effect size of the estimated parameters is the weighted mean response parameter across brands, where the weights represent the reliability of the parameter estimates (see Van Heerde et al. 2013).

5.4 **Measuring the Impact of Moderators on the Brand Damage Effect**

The estimated brand-crisis-specific immediate and cumulative crisis effects are the dependent variables in our moderator analysis. The 214 crisis events determine the sample size of these regressions. We estimate four models, one for immediate and one for cumulative effects, each for brand attention and brand strength. To account for measurement error in the dependent variables and heteroskedastic errors, we weigh each observation with its inverse standard error scaled by effect size:

$$\hat{\beta}^{Imm} = v^{Imm} + \sum_n \delta_n^{Imm} X_n + \sum_n \pi_n^{Imm} B_n + \varepsilon^{Imm} \tag{4}$$

$$\hat{\beta}^{Cum} = v^{Cum} + \sum_n \delta_n^{Cum} X_n + \sum_n \pi_n^{Cum} B_n + \varepsilon^{Cum} \tag{5}$$

[5] For estimation purposes we multiply the parameter γ_{ij} through with the term in the square brackets from Equation (3). Estimating the model, we initially obtain estimates for the different products of parameters.

where $\hat{\beta}^{Imm}$, $\hat{\beta}^{Cum}$ and are the estimated immediate and cumulative coefficients. $X_{n,}$ represents crisis-specific characteristics (crisis type, media coverage, immediate firm reaction, and crisis origin) and B_n are the brand-specific characteristics (brand strength, crisis history, firm size, and product type). The parameters δ^{Imm} , δ^{Cum} ,and π^{Imm} , π^{Cum} are the respective effects of crisis- and brand-specific characteristics on immediate and cumulative crisis impact on our brand metrics. The parameters v^{Imm} and v^{Cum} are intercepts and ε^{Imm} and ε^{Cum} denote the error term, which is assumed to be independently, normally distributed with heteroskedastic variance.

We do allow for error correlation across equations. Note, however, that SUR estimation does not offer an advantage. Since the set of predictor variables for Equation (4) and (5) is identical OLS or WLS estimation, respectively, is as efficient as SUR (Zellner 1962).

5.5 Why not a Panel ECM Framework?

A potential alternative to our estimation procedure could be a one-step Panel ECM that accounts for parameter heterogeneity and interactions among moderator variables and crisis dummies. The advantages come from efficiency gains by pooling brands in a panel and simultaneous one-step estimation. This estimation design, however, is not feasible with our data for several reasons. First, note that a typical panel dataset is composed of a large number of cross sectional units (brands) and short time-series. Efficiency gains mainly arise from the use of cross-sectional variation and by partially imposing homogeneity or distributional assumptions on parameters. Quite in contrast, we have long time-series of 256 periods for 69 brands available. This allows for a reliable estimation of individual parameters. Most importantly, we need not only to estimate individual crisis parameters across brands but also across crises within brands. This is hard to implement in a Panel ECM estimation framework but very easily handled by our equation-by-equation estimation approach. Second, including interactions between crisis dummies and moderator variables introduces severe collinearity issues that overcompensate any potential efficiency gains from one-step estimation. Hence, our estimation procedure appears to be the most efficient approach to obtain the parameter estimates.

6 Results

6.1 Model-free Evidence: Difference-in-Differences Tests

Table 4 shows the results of mean difference tests. Here, we take the difference of the brand attention score and brand strength score, respectively, of the week when the crisis event occurred and the week before. We do this for the focal brand and the group of competitive brands in the respective industry. These brands form our control group.

The results are clear. The crisis event leads, on average, to a significant increase in brand attention ($\Delta = 3.24\%$, $p < .01$) and a significant drop in brand strength ($\Delta = -1.99\%$, $p < .01$). This finding is replicated for each type of crisis. i.e. it holds for product-harm and CSI events as well as for the three CSI types. There are, however, differences between *brand attention* and brand strength when we compare changes across the types of crisis events. We find no significant differences in the magnitude of changes of brand attention for product-harm vs. CSI events ($F_{1,186}$=2.18, $p > .05$) and across all four types of events ($F_{3,186}$=1.17, $p > .05$). The magnitude of changes in *brand strength*, however, is marginally significant for product-harm vs. CSI events ($F_{1,186}$=3.74, $p < .10$) and significant across the four crisis types ($F_{3,186}$=3.75, $p < .05$). It turns out that the drop in brand strength is larger for a CSI event and in particular for environmental scandals as well as violations of human rights and working conditions.

These results provide first evidence on the differential impact of a crisis event on the brand. The analysis, however, is limited to contemporaneous effects and does not control for differences between crises events other than the type of crisis. We therefore turn to the time-series analysis.

Table 4: Changes in Brand Attention and Brand Strength Compared with Industry Average

	Brand attention						***Brand strength***					
	Δ Brand attention [1)]		Δ Focal brand (treatment group) − Δ Industry average (control group)		Difference tests		Δ Brand strength [1)]		Δ Focal brand (treatment group) − Δ Industry average (control group)		Difference tests	
	Focal brand	Industry average	Mean	(SE)	t-value	F-value	Focal brand	Industry average	Mean	(SE)	t-value	F-value
Overall	2.96%	-.14%	3.24%	(.007)	4.68***		-1.76%	.23%	-1.99%	(.004)	-5.45***	
Comparison of product-harm with (average) CSI event												
Product-harm event	1.96%	-.23%	2.19%	(.009)	2.36**	$F_{1,186} = 2.18$ $p = .142$	-.96%	.31%	-1.27%	(.004)	-2.90***	$F_{1,186} = 3.74$ $p = .055$
CSI event	4.17%	-.06%	4.23%	(.010)	4.18***		-2.52%	.16%	-2.67%	(.006)	-4.68***	
Comparison of all four types of events												
Product-harm event	1.96%	-.23%	2.19%	(.004)	2.36**		-.96%	.31%	-1.27%	(.004)	-2.90***	
Violation of fair operating practices	4.73%	-.17%	4.90%	(. 013)	3.79***	$F_{3,186} = 1.17$ $p = .324$	-1.10%	.28%	-1.37%	(.007)	-2.08**	$F_{3,186} = 3.75$ $p = .012$
Violation of human rights / working conditions	3.20%	.10%	3.10%	(.017)	1.83**		-3.52%	.06%	-3.57%	(.009)	-3.82***	
Environmental scandal	6.42%	-.28%	6.70%	(.036)	1.84*		-5.71%	-.01%	-5.70%	(.028)	-2.07**	

Notes: Brand attention and brand strength as in Equation (2) before log-transformation. *** $p < .01$, ** $p < .05$, * $p < .10$ (one-sided if applicable).
[1)] Δ (index measure) = index score at event week – index before event week.

6.2 **Testing for Persistency**

Persistent effects require non-stationary times-series. Thus, we report on our findings of the unit-root tests. Specifically, we test for a unit root in brand attention, brand strength, and advertising expenditures at the individual brand level allowing for brand-specific intercepts and deterministic trends. Specifically, we apply the Augmented Dickey-Fuller (ADF) test, the Phillipps-Perron (PP) test, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (see Patterson 2011). While the ADF and PP tests check for the assumption of a unit root (non stationary time-series), the KPSS tests against the unit root. If either the ADF or PP test suggests a unit root, we apply the KPSS test to check for the alternative assumption. If the KPSS test is rejected we take this as strong evidence for non-stationarity.

We do not find support for the existence of unit roots for any of the three variables in any brand time-series (details are available from the authors). Hence, we establish the first important result. None of the crisis events that occurred in Germany during the 5-year observation period caused a permanent increase in brand attention or a permanent loss in brand strength. As a consequence, brand attention and strength eventually return to their pre-crisis level, controlling for other factors. The long-term parameters of our ECM can be interpreted as the cumulative temporary effects on brand ratings. We discuss findings from this model estimation next.

6.3 **Immediate and Cumulative Effects of Crisis Events on Brand Attention and Strength**

Table 5 presents the overall across-brand parameter estimates of the first stage ECM analysis together with the associated added Z-scores (Rosenthal, 1991). The average adjusted R^2 of .20 is good for a model in first differences. We also checked model fit in a holdout sample based on mean absolute deviation (MAD). Out of-sample MAD for brand attention (brand strength) amounts to .671 (.482) compared to the in-sample MAD of .528 (.429).

Consistent with Berger, Sorensen, and Rasmussen (2010), we find that a crisis event, on average (across all four types), has a positive impact on brand attention, both immediately ($\beta^{\text{Imm}}_{\text{Attention}}$ = .035, p < .01) and cumulative ($\beta^{\text{Cum}}_{\text{Attention}}$ = .075, p < .01). The average effect on brand strength is negative and significant for immediate ($\beta^{\text{Imm}}_{\text{Strength}}$ = -.017, p < .01) and cumulative ($\beta^{Cum}_{Strength}$ = -.044, p < .01) effects. These results are consistent with prior findings on consumer attitudinal responses to brand crises (e.g., Ahluwahlia, Burnkraut, and Unnava 2000; Cleeren, Dekimpe, and Helsen 2008). By using the adjustment parameter in combination with the estimated cumulative effect, we obtain an estimate for the duration of the effects. Note while the adjustment parameter is brand-specific the β^{Cum}-parameters for long-term effects in Equation (3) are not. They are crisis-specific. Thus, durations also vary across crises within the same brand. The increase in brand attention ranges from .5 months to 9.5 months in our sample. Its average is 2 months. Brand strength effects last from .5 months to 9.25 months. On average, it takes 2.6 months for the brand to recover from the loss.

The influence of the controls advertising expenditures and industry brand attention and strength is as expected. On average, advertising shows positive immediate and long-term effects on both brand attention and brand strength. The impact comes out stronger for attention. Both brand metrics are also significantly influenced by their industry averages. Hence, it is important to control for them. Note that both advertising expenditures and industry averages of the two metrics are instrumented to address simultaneity issues.

Table 5: 2SLS Estimation Results for Error Correction Models

		Brand attention			Brand strength		
	Obs	*Expected sign*	*Estimated average coefficient*	*Z-Score*	*Expected sign*	*Estimated average coefficient*	*Z-Score*
Intercept	69	+/-	-.1048	-3.20 ***	+/-	.0166	3.90 ***
Advertising expenditures							
Immediate	69	+	.0079	5.44 **	+	.0002	2.21 **
Cumulative	69	+	.0229	6.49 ***	+	.0014	11.06 ***
Industry brand attention							
Immediate	69	+	.0613	27.73 ***		-	-
Cumulative	69	+	.0245	2.46 ***		-	-
Industry brand strength							
Immediate	69		-	-	+	.0224	30.23 ***
Cumulative	69		-	-	+	.0142	3.76 ***
Crisis event							
Immediate	214	+	.0350	13.02 ***	-	-.0166	-33.59 ***
Cumulative	214	+	.0750	11.02 ***	-	-.0437	-22.34 ***
Adjustment	69	-1< g <0	-.5610	-34.26 ***	-1< g <0	-.4041	-55.42 ***
Long-term Trend	69	no	-.1147	-14.15 ***	no	.0072	2.56 ***

Notes: ** p < .05, *** p < .01 (two-sided).

6.4 Explaining the Magnitude of Crisis Effects

Brand attention. Table 6 presents the results from estimating the impact of the moderator variables on the magnitude of immediate and cumulative brand effects. Both the immediate and cumulative attention effect seems to be larger for violations of human rights and working conditions compared to product issues. There is no difference in immediate effects for the other two CSI crisis types. The cumulative effect for violations of fair operating practices is significantly lower than for product issues. Overall, however, there is no consistent difference between product-harm events and CSI events. The estimated average CSI crisis effect is not significantly different from the effect of product-harm events. Hence, both product-harm and CSI events raise brand attention to a similar average level.

Among the other moderator variables, we find support for our expectations with respect to media coverage and prior brand strength. The attention effect is larger the broader the crisis event is covered in the media. The attention effect, however, is smaller for stronger brands. Hence, weaker and less-known brands benefit more from the pure attention effect (Berger, Sorensen, and Rasmussen 2010). We also find that an immediate acceptance of firm's responsibility reduces the immediate attention effect. The effect, however, is larger in the long run if the firm denies responsibility as immediate reaction.

Brand strength. Consistent with our model-free analysis (see Table 4 again), we find support for differences in crisis impact on brand strength depending on the type of the crisis. For the immediate effect, the violation of human rights and working conditions and environmental scandals lead to a significantly larger drop in brand strength compared to product-harm crises. For the cumulative effect, these differences hold and become even larger for environmental scandals. Thus, CSI-related crisis events have, on average, a stronger immediate and cumulative negative effect on brand strength than product-harm events. The estimated average effect across the three CSI crises supports this conclusion (see Table 6).

Table 6 also informs about the role of other crisis and brand/firm characteristics. Consistent with our expectation, we find strong support for the role of media coverage and crisis origin. Both larger media coverage and a national crisis event increase the immediate and cumulative brand strength effects. We also find that the immediate firm reaction has an influence on the immediate and cumulative brand effect. Accepting responsibility reduces brand strength damage in the short run. But it increases the damage in the long run if the firm denies responsibility.

Brand and firm characteristics primarily drive the cumulative brand damage effect. Here, stronger brand strength helps lowering the impact of the crisis event. Similarly, firms benefit from size, i.e. the negative effects on brand strength are less for larger firms. In contrast, if a firm has a crisis history the cumulative brand damage becomes larger.

6.5 Assessing the Magnitude of Crisis Effects

The practical significance of the estimation results in Table 6 is not obvious. We therefore use the parameter estimates of Table 5 and 6 together with model (1) to simulate brand effects. Figure 4 and 5 show the results. We first simulate the base scenario. Here, we set all variables at their sample mean. In fact, this produces the average increase in brand attention and loss in brand strength across all crises and brands. We then change only one driver variable. For non-metric variables such as the type of crisis, we set the focal category to 1 and all other categories to 0. For the metric variables such as media coverage, the equivalent is to increase the value by 100%. Relating this change to the relative change in brand attention and brand strength scores produces an arc estimate for the associated elasticity. In addition, we compute the implied changes in the duration of the crisis effects.

Brand attention. The left bar diagram in Figure 4 shows that immediate attention for a brand due to a crisis event increases, on average, by 10% in our sample. The increase lasts for 2.1 months, on average, and builds up to a cumulative increase of 43%. This is a substantial effect. Consistent with the results Table 6, there are no significant differences in the effects among product-harm and CSI crisis events. Figure 4, however, demonstrates that media coverage and immediate firm reaction are important drivers of the attention effect. 100% higher media coverage increases attention levels to 44% (immediate effect) and 147% (cumulative effect), respectively. As a result, the duration of the attention effect is much longer with almost 8 months. A similar strong increase in cumulative brand attention occurs if the firm denies responsibility (88%). The higher attention level lasts for 4.6 months in this case.

Brand strength. As shown by the left bar diagram in Figure 5, on average, a brand in our sample looses -13% of its brand strength immediately after the crisis event. If we assume a product-harm event, the loss reduces to -7%, but it increases to -19% for a CSI-related event. By all means, these are sizeable damage effects to brand strength. The difference between CSI and product-harm events is remarkable. The whole extent of the damage becomes apparent in the middle bar diagram. It illustrates the cumulative loss of brand strength until the brand returns to its equilibrium level. The average brand looses -36% of its brand strength in total in a product-harm crisis. For an ethical crisis, this cumulative loss increases to -87%. Brands return to their equilibrium strength level after 1.2 months in a product-harm crisis and after 3.4 months in a CSI crisis.

These damages are considerably amplified if more media cover the event, the event is a national event, and the brand has a crisis history. Media coverage is again by far the greatest driver of the crisis impact. The immediate damage amounts to -21% and the cumulative damage to -109% if media coverage doubles. The effect lasts for 4.3 months in this case. Note that the loss in brand strength may be greater than -100% because the BrandIndex runs from -100 to +100. These figures correspond to elasticities of -.61 (=-20%/-13%-1) and -.84, respectively. The second largest driver is firm reaction. If the immediate reaction is to deny responsibility, the cumulative loss in brand strength amounts to -86% and lasts for 3.3 months. Cumulative loss in brand strength reaches -64% for a national event and -74% for a larger crisis history.

There are also drivers that attenuate the damage effect. If firms immediately accept responsibility for their wrongdoing they can reduce the immediate damage effect to -2%. Moreover, a strong brand helps. It limits the cumulative loss in brand strength to -48%, which is equivalent to an elasticity of .19.

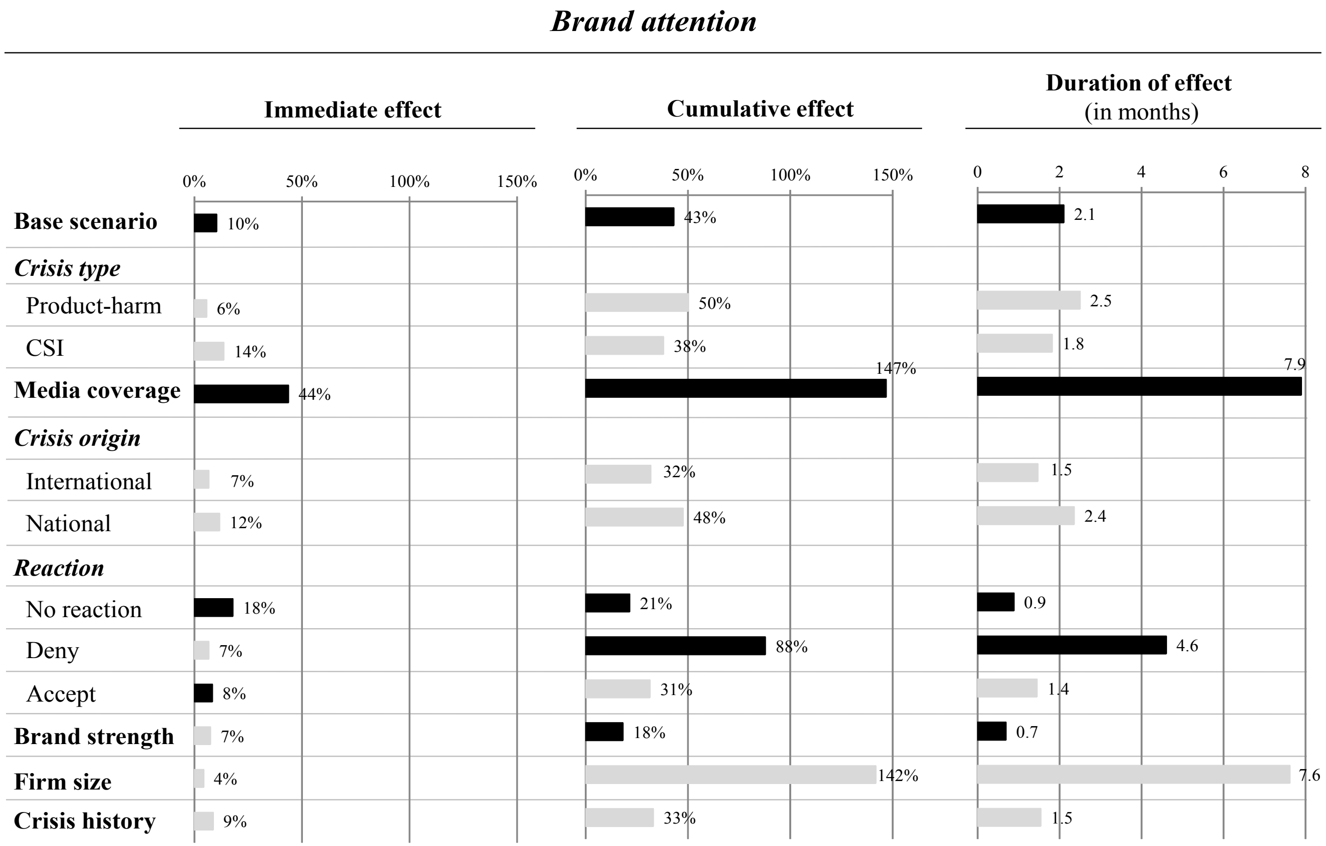
Table 6: WLS Estimation Results for Drivers of Brand Effects

			Brand attention					***Brand image***			
Dependent variable:			*Estimated immediate effect*		*Estimated cumulative effect*			*Estimated immediate effect*		*Estimated cumulative effect*	
		Expected sign	*Coefficient*		*Coefficient*		*Expected sign*	*Coefficient*		*Coefficient*	
Intercept		+/-	-.125	(.115)	-.983 *	(.514)	+/-	-.110 **	(.045)	-.318	(.244)
Crisis type	*Product-harm crisis (base)*		-	-	-	-		-	-	-	
	CSI (average)	+/-	.046	(.036)	-.072	(.181)	+/-	-.055 ***	(.011)	-.238 **	(.108)
	Violation of fair operating practice	+/-	.038	(.041)	-.478 ***	(.138)	+/-	.002	(.013)	-.052	(.067)
	Violation of human rights / working conditions	+/-	.132 ***	(.035)	.346 **	(.138)	+/-	-.127 ***	(.013)	-.128 *	(.075)
	Environmental scandal	+/-	-.031	(.084)	-.084	(.351)	+/-	-.041 **	(.019)	-.526 ***	(.153)
	Product-harm and CSI crisis	+/-	-.042	(.046)	-.380 **	(.155)	+/-	.008	(.014)	.047	(.075)
Crisis characteristics											
Media coverage		+	.030 ***	(.004)	.097 ***	(.014)	-	-.006 ***	(.001)	-.035 ***	(.008)
Crisis origin	*International (base)*		-		-			-		-	
	National	+/-	.029	(.033)	.093	(.116)	-	-.059 ***	(.012)	-.086 *	(.052)
Immediate firm reaction	*No reaction (base)*		-	-	-	-		-	-	-	-
	Deny responsibility	+/-	-.065	(.040)	.395 ***	(.127)	+/-	-.014	(.010)	-.156 **	(.068)
	Accept responsibility	+/-	-.056 ***	(.028)	.058	(.115)	+/-	.062 ***	(.011)	.050	(.052)
Brand & firm characteristics											
Product type	*Retail (base)*	-	-	-	-	-	-	-	-	-	-
	Non-Durables	+/-	-.064	(.062)	-.046	(.211)	+/-	.047 *	(.028)	.212	(.149)
	Durables	+/-	-.016	(.036)	.336 ***	(.128)	+/-	-.025 **	(.011)	.034	(.071)
	Services	+/-	-.033	(.044)	-.309 *	(.171)	+/-	.005	(.015)	.250 ***	(.093)
Prior brand strength		-	-.001 *	(.001)	-.010 ***	(.003)	+	3.4×10^{-4}	(2.8×10^{-4})	.004 **	(.002)
Firm size		-	-.003	(.010)	.054	(.043)	+/-	.013 ***	(.003)	.035 *	(.019)
Crisis history		+/-	-.003	(.004)	-.021	(.016)	-	9.1×10^{-5}	(.001)	-.024 ***	(.008)
$\mathbf{R^2}$			*.552*		*.300*			*.677*		*.261*	
N			*214*		*214*			*214*		*214*	

Note: * p<.1, ** p<.05, *** p<.01. Tests are one-sided if clear directional effects are expected, two-sided if not. Standard errors in parentheses.

[1)] The coefficient for CSI (average) is the mean of the estimated coefficients for the three CSI-crisis types. The standard error is calculated from the associated variance-covariance matrix. We also estimated a model that includes a dummy variable for CSI event only (instead of three different types). Results are fully consistent with this table.

Figure 4: Brand Attention Effects (Simulation of Gains and Losses)

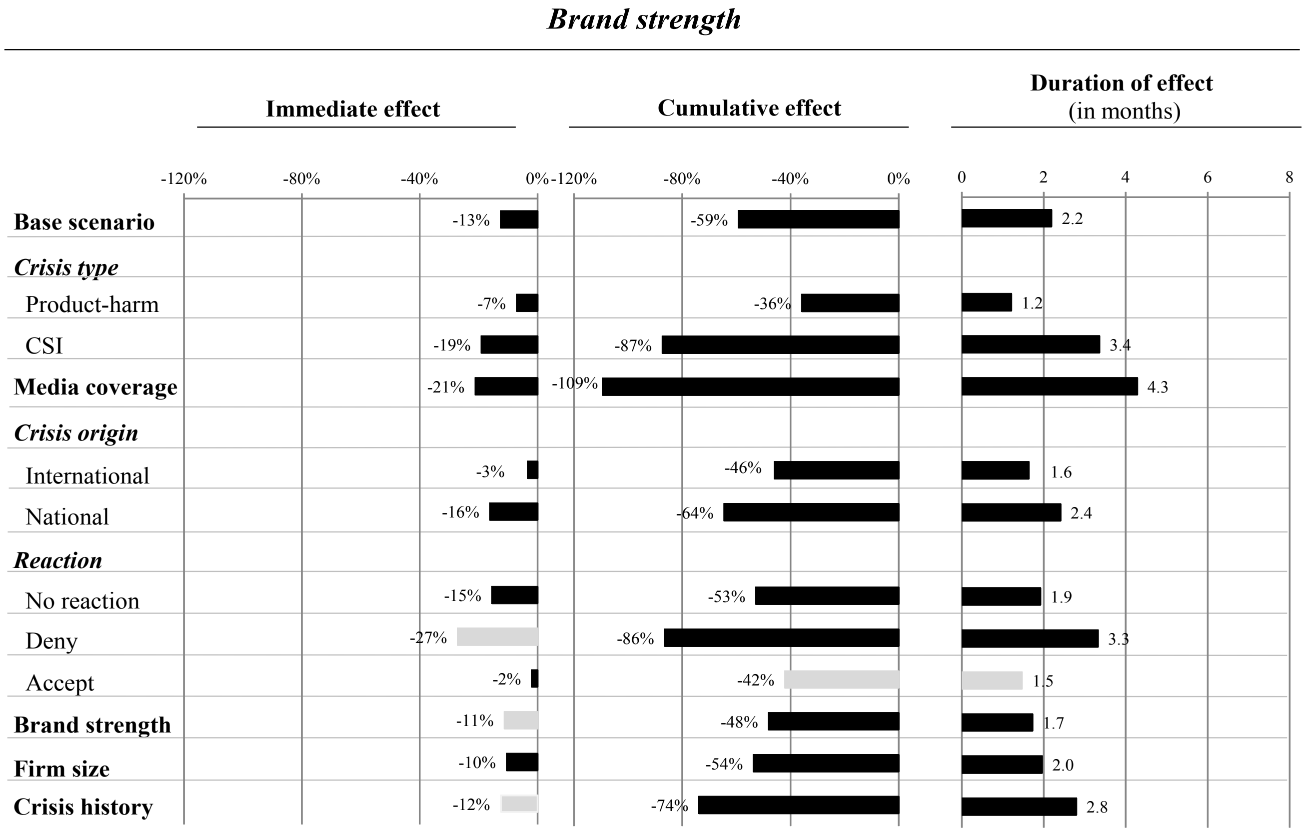


- Base scenario measures the grand mean by keeping all variables at their sample mean.
- Analysis simulates increase in brand attention if focal moderator variable takes on value of new category or increases by 100%.
- Duration is estimated based on cumulative effect relative to grand mean.
- Colors indicate whether estimated coefficients are significant with respect to 2nd stage WLS regression.

significant effect   non-significant effect

Note: Cumulated brand increase cumulates percentage gains in brand attention over the whole period until brand attention returns to pre-crisis level.

Figure 5: Brand Strength Effects (Simulation of Gains and Losses)



- Base scenario measures the grand mean by keeping all variables at their sample mean.
- Analysis simulates loss in brand strength if focal moderator variable takes on value of new category or increases by 100%.
- Duration is estimated based on cumulative effect relative to grand mean.
- Colors indicate whether estimated coefficients are significant with respect to 2nd stage WLS regression.

■ significant effect ■ non-significant effect

Note: Loss in brand strength may even be greater than -100% because the brand strength index runs from -100 to +100. Cumulated brand damage cumulates percentage losses in brand strength over the whole period until brand attention returns to pre-crisis level.

6.6 **Robustness Checks**

We checked the robustness of our results in several ways (see the Appendix for details). We estimated Panel ECMs including 2 and 4 crisis dummy variables that are brand-specific. We also estimated our model (3) using media coverage instead of the respective crisis event dummy. In addition, we estimated model (3) for those crises, which did not pass our 3 media outlet threshold. Finally, we added additional moderators to our 2nd-stage equations (4) and (5). These are change in firm reaction over time, factual evidence of accusations, and organizational depth of responsibility. None of these analyses suggest any different conclusions.

7 **Discussion**

7.1 **Conclusions**

Our study generates novel and surprising insights. First, we conclude that the effect of a crisis is asymmetric. It increases brand attention but damages brand strength, both immediately and in the long run. This finding is consistent with prior literature that negative news raises attention but hurts product evaluation (Chintagunta, Gopinath, and Venkataraman 2010).

An important question, however, remains to be answered. What is the ultimate effect on economic performance such as sales? Apparently, the net effect should be more detrimental if higher attention is paired with news of a negative connotation. Berger, Sorensen, and Rasmussen (2010), however, argue that sales might increase for smaller, unknown products because awareness and negative publicity valence tend to become dissociated in memory for them. Unfortunately, we have no sales data available for our sample of brands to test this supposition. But we can check the association between positive crisis attention effects and negative brand strength effects in our sample. The same three events for BP, Toyota, and Aral are among the top 5 events for both brand attention and brand strength effects. This suggests events that cause the largest damage to brand strength also tend to induce the highest brand attention. Indeed, the correlation between cumulative attention and strength effects amounts to -.53 ($p < .01$) in the total sample and strongly supports the negative association. Thus, we conclude that the net effect of a crisis event on (economic) brand performance is likely to be damaging.[6]

Third, there seems to be no systematic difference between the attention effect of a product-harm event and a CSI event. But the potential brand damage from CSI-related crises is, on average, deeper and cumulates to a larger total effect over time than for product-harm crises. This result is surprising and challenges conventional wisdom that unethical firm behavior does not impact customer behavior as strong as a product-harm event.

Fourth, we do not find support for the persistency of brand damage effects – at least during our observation period. While we do not want to generalize this to other countries or periods, it seems to be consistent with the observation that consumers tend to forget about the crisis sooner or later (Vassilikopoulou et al. 2009). There are many examples from food-poisoning scandals where consumer demand returned to its pre-crises level after a relatively short time period. Nevertheless, a crisis event causes brand damage for 2-3 months, which may extend to 9 months.

Finally, there are important conditions that may turn a crisis into a more severe crisis. Media coverage generally amplifies the crisis, both in terms of attention and damage to brand strength. In contrast, a strong brand, however, protects against the loss in brand strength and reduces brand attention. There has been a vivid discussion on which is the best firm response

[6] In a separate analysis, we re-estimated model (3) by using the brand recommendation item of the YouGov BrandIndex as dependent variable (see Appendix). The results are very similar to our results for brand strength. This suggests that long-term sales effects are likely to suffer from the crisis event since repurchases and sales from new customers should be lower if recommendation rates drop.

for companies to a crisis (Cleeren, van Heerde, and Dekimpe 2013). Across industries and products, our results suggest that denying any responsibility is the worst option. Accepting responsibility or at least not responding in a confronting way seems to protect from larger brand damage.

7.2 Managerial Implications

Our study provides important implications for managers. First and foremost, we warn against ignoring the risks of corporate socially irresponsible behavior. Our results offer a clear message that such behavior may have a devastating effect on one of the most valuable corporate assets, the brand. There is an asymmetric focus on CSR and cause-related marketing activities in research and in practice (Lange and Washburn 2012). In the light of our findings, this partial attention is no longer warranted; the more so as the impact of CSR measures is rather modest.

While a product-harm crisis often shows an immediate impact on sales and profit since product recalls result in extra costs and lost sales (e.g., Van Heerde, Helsen, and Dekimpe 2007), this does not need to extend to a CSR-related crisis. It is, however, myopic to conclude that there are no sales effects. The harm to brand strength translates into a sales loss that rather subtly unfolds over time. The use of a mindset-metric model (e.g., Hanssens et al. 2014) may help in describing and predicting the sales impact of changes in brand strength over time.

Our results are also valuable to managers because they help understand which events have the potential to develop into a deep and long crisis. We do not claim that every event of corporate social misconduct poses a threat to the brand. But there are conditions such as the type of crisis and media coverage that favor the occurrence of a severe crisis. The violation of environmental surroundings, which includes in our definition unethical husbandry conditions, is very likely to turn into a major crisis. Similarly, the more media pick up on the crisis event the greater the chance that it becomes a severe crisis. Media coverage essentially has a double jeopardy effect as it also intensifies brand attention. Marketing management thus should closely follow the media coverage and maintain contact to journalists. Given the dangerous impact on the brand, this task should not be outsourced to the PR department in the firm.

While media coverage probably is a universal catalyzer of a crisis, other conditions depend on the value system of consumers in a country. We acknowledge that the strong impact of environmental crises on the brand is specific to the German consumer and not necessarily shared by consumers of other countries.

Our study also shows that denying the responsibility of a crisis in the beginning hurts the brand over time. There is no evidence for one specific dominant strategy of how a firm should immediately react to a crisis event. While there is some evidence that brand damage can be reduced if the firm accepts or at least does not deny responsibility, we believe that there are further crisis characteristics that have to be taken into account. The best response for management depends on these conditions. Future research might inform about these conditions and derive appropriate strategies.

7.3 Limitations and Further Research

While our study offers valuable insights on how different crisis types affect consumers' brand perception, it also has limitations that offer interesting avenues for further research. Our empirical application is limited to media analysis and consumer responses in Germany. Since, consumer responses might differ due to cultural differences, it would be worthwhile to extend our analysis to other countries and cultures.

Our study focuses on brand metrics as intermediate performance measures. Future studies might investigate the effects of CSI-related crises on other performance metrics such as satisfaction, loyalty, or sales.

Finally, our results apply to those brands that are picked up by media in a potential crisis situation. Media are probably selective in their decisions to report on a brand crisis and tend to prefer larger and better-known brands. A logical next question would be to ask for the criteria and conditions that editorial journalists apply to report on a brand crisis story. Our study leaves this question to be answered by future research.

References Paper I

Ahluwalia, Rohini (2002), "How Prevalent Is the Negativity Effect in Consumer Environments?," *Journal of Consumer Research*, 29 (2), 270-79.

Ahluwalia, Rohini, Robert E. Burnkrant, and H. Rao Unnava (2000), "Consumer Response to Negative Publicity: The Moderating Role of Commitment," *Journal of Consumer Research*, 37 (2), 203-14.

Basuroy, Suman, Subimal Chatterjee, and S. Abraham Ravid (2003), "How Critical Are Critical Reviews? The Box Office Effects of Film Critics, Star Power, and Budgets." *Journal of Marketing*, 67 (4), 103-17.

Bazerman, Max H. and Anne Tenbrunsel (2011), "Ethical breakdowns," *Harvard Business Review*, 89 (4), 58–65.

Berger, Jonah, Alan T. Sorensen, and Scott J. Rasmussen (2010), "Positive Effects of Negative Publicity: When Negative Reviews Increase Sales," *Marketing Science*, 29 (5), 815-27.

Bonini, Sheila, David Court, and Alberto Marchi (2009), "Rebuilding Corporate Reputations," *The McKinsey Quarterly*, June.

Borah, Abhishek, and Gerard J. Tellis (2016),"Halo (Spillover) Effects in Social Media: Do Product Recalls Hurt or Help Rival Brands?" *Journal of Marketing Research*, 52 (2), 143-60.

Chen, Yubo, Shankar Ganesan, and Yong Liu (2009), "Does a Firm's Product Recall Strategy Affect its Financial Value? An Examination of Strategic Alternatives during Product-harm Crises," *Journal of Marketing*, 73 (6), 214-26.

Chintagunta, Pradeep K, Shyam Gopinath, and Sriram Venkataraman (2010), "The Effects of Online User Reviews on Movie Box Office Performance: Accounting for Sequential Rollout and Aggregation Across Local Markets," *Marketing Science*, 29 (5), 944-57.

Cleeren, Kathleen, Marnik G. Dekimpe, and Kristiaan Helsen (2008), "Weathering Product-Harm Crisis," *Journal of the Academy of Marketing Science*, 36 (2), 262-70.

Cleeren, Kathleen, Harald J. Van Heerde, and Marnik G. Dekimpe (2013), "Rising from the Ashes: How Brands and Categories Can Overcome Product-harm Crises," *Journal of Marketing*, 77 (2), 58-77.

Dawar, Niraj and Madan M. Pillutla (2000), "Impact of Product-Harm Crises on Brand Equity: The Moderating Role of Consumer Expectations," *Journal of Marketing Research*, 37 (2), 215-26.

Dutta, Sujay and Chris Pullig (2011), "Effectiveness of Corporate Responses to Brand Crises: The Role of Crisis Type and Response Strategies," *Journal of Business Research*, 64 (12), 1281-87.

Fan, David, David Geddes, and Felix Flory (2013), “The Toyota Recall Crisis: Media Impact on Toyota’s Corporate Brand Reputation,” *Corporate Reputation Review*, 16(2), 99-117.

Flammer, Caroline (2013), “Corporate Social Responsibility and Shareholder Reaction: The Environmental Awareness of Investors,” *Academy of Management Journal*, 56 (3), 758–81.

Gijsenberg, Maarten J. (2014), “Going for Gold: Investigating the (Non)Sense of Increased Advertising around Major Sports Events,” *International Journal of Research in Marketing*, 31 (1), 2-15.

Gijsenberg, Maarten J., Harald J. Van Heerde, and Peter C. Verhoef (2015), “Losses Loom Longer Than Gains: Modeling the Impact of Service Crises on Perceived Service Quality over Time,“ *Journal of Marketing Research*, 52 (5), 642-56.

Greene, William H. (2012), *Econometric Analysis*, 7th ed. New York: Prentice Hall.

Hanssens, Dominique M., Leonard J. Parsons, and Randall L. Schultz (2001), *Market Response Models, Econometric and Time Series Analysis.* 2nd ed., Boston et al.: Kluwer.

Hanssens, Dominique M., Koen H. Pauwels, Shuba Srinivasan, Marc Vanhuele, and Gokhan Yildrim (2014), “Consumer attitude metrics for guiding marketing mix decision,” *Marketing Science*, 33 (4), 534-50.

Hsu, Liwu and Benjamin Lawrence (2015), “The Role of Social Media and Brand Equity During a Product Recall Crisis: A Shareholder Value Perspective,” *International Journal of Research in Marketing*, 33 (1), 59-77.

Kang, Charles, Frank Germann, and Rajdeep Grewal (2016), “Washing Away Your Sins? Corporate Social Responsibility, Corporate Social Irresponsibility, and Firm Performance.” *Journal of Marketing*, 80 (2), 59-79.

Kalaignanam, Kartik, Tarun Kushwaha, and Meike Eilert (2013), “The Impact of Product Recalls on Future Product Reliability and Future Accidents: Evidence from the Automobile Industry,” *Journal of Marketing*, 77 (2), 41–57.

Keller, Kevin Lane (1993), “Conceptualizing, Measuring, and Managing Customer-based Brand Equity,” *Journal of Marketing*, 57 (1), 1-22.

Lange, Donald and Nathan T. Washburn (2012), “Understanding Attributions of Corporate Social Irresponsibility,” *Academy of Management Review*, 37 (2), 300-26.

Lei, Jing, Niraj Dawar, and Jos Lemmink (2008), “Negative Spillover in Brand Portfolios: Exploring the Antecedents of Asymmetric Effects,” *Journal of Marketing*, 72 (3), 111-23.

Lei, Jing, Niraj Dawar, and Zeynep Gürhan-Canli (2012), “Base-Rate Information in Consumer Attributions of Product-Harm Crises,” *Journal of Marketing Research*, 49 (3), 336-48.

Liu, Angela Xia, Ying Lui, and Ting Luo (2016), “What Drives a Firm’s Choice of Product Recall Remedy? The Impact of Remedy Cost, Product Hazard, and the CEO.” *Journal of Marketing*, 80 (3), 79-95.

Liu, Yan and Venkatesh Shankar (2015), "The Dynamic Impact of Product-harm Crises on Brand Equity and Advertising Effectiveness: An Empirical Analysis of the Automobile Industry," *Management Science*, 61 (10), 2514–35.

McWilliams, Abagail and Donald Siegel (1997), "Event Studies in Management Research: Theoretical and Empirical Issues", *The Academy of Management Journal*, 40 (3), 626-57.

Muller, Alan and Roman Kräussl (2011), "Doing Good Deeds in Times of Need: A Strategic Perspective on Corporate Disaster Donations," *Strategic Management Journal*, 32 (9), 911-29.

Nelson, Phillip (1970), "Information and Consumer Behavior," *Journal of Political Economy*, 78 (2), 311-29.

Patterson, Kerry (2011), *Unit Root Tests in Time Series: Volume 1*, Basingstoke: Palgrave MacMillan.

Pauwels, Koen, Shuba Srinivasan, and Philip Hans Franses (2007), "When Do Price Thresholds Matter in Retail Categories?," *Marketing Science*, 26 (1), 83-100.

Pullig, Chris, Richard G. Netemeyer, and Abhijit Biswas (2006), "Attitude Basis, Certainty, and Challenge Alignment: A Case of Negative Brand Publicity," *Journal of the Academy of Marketing Science*, 34, 528-42.

Rhee, Mooweon, and Pamela R. Haunschild (2006), "The Liability of Good Reputation: A Study of Product Recalls in the U.S. Automobile Industry," *Organization Science*, 17 (1), 101-17.

Roehm, Michelle L. and Alice M. Tybout (2006), "When Will a Brand Scandal Spill Over, and How Should Competitors Respond?," *Journal of Marketing Research*, 43 (3). 366-73.

Rosenthal, Robert (1991), "*Meta-analytic Procedures for Social Research*," Newbury Park: Sage Publications.

Rubel, Olivier, Prasad A. Naik, and Shuba Srinivasan (2011), "Optimal Advertising When Envisioning a Product-Harm Crisis," *Marketing Science*, 30 (6), 1048-65.

Rust, Roland T., Katherine N. Lemon, and Valarie A. Zeithaml (2004), "Return on Marketing: Using Customer Equity to Focus Marketing Strategy." *Journal of Marketing*, 68 (1), 109-27.

Stahl, Florian, Mark Heitmann, Donald R. Lehmann, and Scott A. Neslin (2012), "The Impact of Brand Equity on Customer Acquisition, Retention, and Profit Margin," *Journal of Marketing*, 76 (4), 44-63.

Thirumalai, S., K. and K. Sinha (2011), "Product recalls in the medical device industry: An empirical exploration of the sources and financial consequences," *Management Science*, 57 (2), 376-92.

Thompson, Craig J., and Zeynep Arsel (2004), "The Starbucks Brandscape and Consumers' (Anticorporate) Experiences of Glocalization" *Journal of Consumer Research*, 31 (3), 631-42.

Van Heerde, Harald J., Kristiaan Helsen and Marnik G. Dekimpe (2007), "The Impact of a Product-Harm Crisis on Marketing Effectiveness," *Marketing Science*, 26 (2), 230-45.

Van Heerde, Harald J., Maarten J. Gijsenberg, Marnik G. Dekimpe, and Jan-Benedict E.M. Steenkamp (2013), "Price and Advertising Effectiveness over the Business Cycle," *Journal of Marketing Research*, 50 (2), 177-93.

Vassilikopoulou, Aikaterini, George Siomkos, Kalliopi Chatzipanagiotou, and Angelos Pantouvakis (2009), "Product-harm crisis management: Time heals all wounds?" *Journal of Retailing and Consumer Services*, 16 (3), 174-80.

Zautra, Alex J., Glenn G. Affleck, Howard Tennen, John W. Reich, and Mary C. Davis (2005), "Dynamic approaches to emotions and stress in everyday life," *Journal of Personality*, 73 (6), 1511-38.

Zellner, Arnold (1962), "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias," *Journal of the American Statistical Association*, 57 (298), 348- 68.

Zhao, Yi, Ying Zhao, and Kristiaan Helsen (2011), "Consumer Learning in a Turbulent Market Environment: Modeling Consumer Choice Dynamics After a Product-Harm Crisis," *Journal of Marketing Research,* 48 (2), 255-67.

Appendix Paper I

Appendix A: Details on the YouGov Brand Metric Measure

In the following, we describe the procedure YouGov used from 2008-2012 to collect brand attention and brand strength information. The company changed the methodology by expanding the set of items in 2013.

YouGov's BrandIndex is a daily measure of brand strength among the public, tracking many brands across multiple consumer sectors simultaneously. For the German market, YouGov monitors about 600 brands in 12 industry sectors, which cover the bandwidth of B2C industries by surveying approximately 2,000 consumers (panel size of 170,000) daily. The BrandIndex consists of six items: perceived brand quality, brand value, brand satisfaction, brand recommendation, brand identification, and brand overall impression. Additionally, YouGov also asks respondents with respect to a seventh item: brand attention. Table A.1 provides details on the exact question for each item.

The data collection of YouGov can be described as follows: For each item a minimum of 100 respondents per day are randomly drawn from the panel and provided with a set of up to 25 brands for a pre-selected industry. To reduce common method bias respondents evaluate only one brand item per industry per enquiry. First, respondents select those brands (per click) for which they agree with the positive statement of the brand item (e.g., good brand quality). Then, they select those brands for which they agree with the negative statement of the brand item (e.g., poor brand quality). The aggregate raw brand strength measure (YouGov BrandIndex) is calculated by counting the number of respondents who agree with the six positive statements (items) and the number of respondents who agree with the six negative statements (items) divided by the total number of respondents (= number of positive + negative + neutral respondents) multiplied by 100. As a consequence, the YouGov BrandIndex brand strength measure is a ratio-scaled variable and lies within the range of -100 to +100. The brand attention metric is calculated by summing up all positive and negative responses divided by the total number of respondents (= number of positive + negative + neutral responses).

The collection procedure yields about 600 daily responses across seven brand items, which results in 3,000 responses in our weekly aggregation. To ensure representativeness individual sampling weights are applied to correct for variations in the probability selection of respondents. Although panelists might be re-invited after a period of two weeks, they will be blocked for the respective sector and brand item they have answered before for a period of at least two months. This is important to eliminate repeated measurement as a source for demand effects and serial correlation in brand perceptions. Brand competition effects are also controlled for because respondents rate the competing brands within one sector simultaneously.

Table A1
ITEMS FOR MEASURING BRAND ATTENTION AND BRAND STRENGTH
(YOUGOV's BRANDINDEX)

Dimension	*Questions*
Brand attention	About which of the following brands have you recently heard anything positive or negative either through media news, advertising, or word-of-mouth?
Brand quality	Which of the following brands do you think stand for good quality? Now, which of the following brands stand for poor quality?
Brand value	Which of the following brands do you think provide good value for money (or you would be willing to invest parts of your spare time)? † Now, which of the following brands do you think provide poor value for money (or you would be willing to invest parts of your spare time)? ††
Brand satisfaction	Choose all brands you are satisfied with or for which you believe you would be satisfied if you were a customer? Choose all brands you are dissatisfied with or for which you believe you would be dissatisfied if you were a customer?
Brand recommendation	Which of the following brands would you recommend to a friend or colleague? And which of the following brands would you recommend a friend or colleague to avoid?
Brand identification	Which of the following brands would you be proud of to work for or to be associated with? ††† Now, which of the following brands would you be embarrassed to work for or be associated with? †††
Brand overall impression	Overall, of which of the following brands do you have a positive impression? Now, of which of the following brands do you have an overall negative impression?

Note: Additional explanations provided to the respondent include:
† By that we don't mean "cheap," but that the brands offer a customer a lot in return for the price paid.
†† By that, we don't mean "expensive," but that the brands do not offer a customer much in return for the price paid.
††† Imagine you (or your friend) were applying for the same sort of role at the following brands that you currently have or would apply for.

Appendix B: Construct Validity: Exploratory and Confirmatory Factor Analysis

First, in order to validate our constructs (brand strength and brand attention) we apply exploratory factor with Varimax rotation on the brand items collected by YouGov. Correlations between the items are presented in Table B1. The results in Table B2 suggest a two-factor solution. Factor 1 includes the six BrandIndex items and encompasses our brand strength construct: quality, value, identification, overall impression, satisfaction, and recommendation. Factor 2 represents just the single item brand attention. Cronbachs Alpha for brand strength is very high with .975. These findings are stable across brands and within brands over time. Based on this exploratory analysis, we additionally applied confirmatory factor analysis to validate the two factor structure. Models and parameter estimates clearly pass the common thresholds (Fornell and Larcker, 1981; Bagozzi and Yi, 1988; Hu and Bendtler 1999) for model fit, parameter reliability, and construct validity (see Table B3).

Table B1
CORRELATION OF BRAND DIMENSIONS (YOUGOV)

N = 17,043	1. Attention	2. Impression	3. Recommendation	4. Identification	5. Quality	6. Value	7. Satisfaction
1. Attention	1.0	-	-	-	-	-	-
2. Impression	.12	1.0	-	-	-	-	-
3. Recommendation	.19	.97	1.0	-	-	-	-
4. Identification	-.15	.82	.77	1.0	-	-	-
5. Quality	.08	.93	.91	.86	1.0	-	-
6. Value	.19	.90	.92	.67	.80	1.0	-
7. Satisfaction	.21	.95	.95	.74	.89	.93	1.0

Table B2
FACTOR ANALYSIS RESULTS FOR DIFFERENT BRAND DIMENSIONS (YOUGOV)

Dimension	Factor 1 Brand attention (1.10)	Factor 2 Brand strength (5.37)
Brand quality	-.02	**.96***
Brand value	.38	**.87***
Brand identification	-.30	**.89***
Brand impression	.16	**.97***
Brand satisfaction	.30	**.93***
Brand recommendation	.24	**.95***
Brand attention	**.52***.	.05

Note: In the parenthesis below the factor we report eigenvalues that are > 1 for both factors. * indicates highest loading

Table B3
SUMMARY RESULTS FOR CONFIRMATORY FACTOR ANALYSIS

Reliability of parameters	Construct validity	Model fit
Critical ratios $\geq$ 1.96	Construct reliability = .977	SRMR = .485
AVEs $\geq$ .626	Average AVE = .863	TLI = .950
	φ^2 = .029	CFI = .967
	Discriminant validity Fornell/Larcker criterion (Average AVE > φ^2) = ✓	

Notes: AVE = Average variance extracted, φ^2 = squared factor correlation, SRMR = Standardized root mean squared residual, TLI = Tucker-Lewis index, CFI = Comparative fit index.

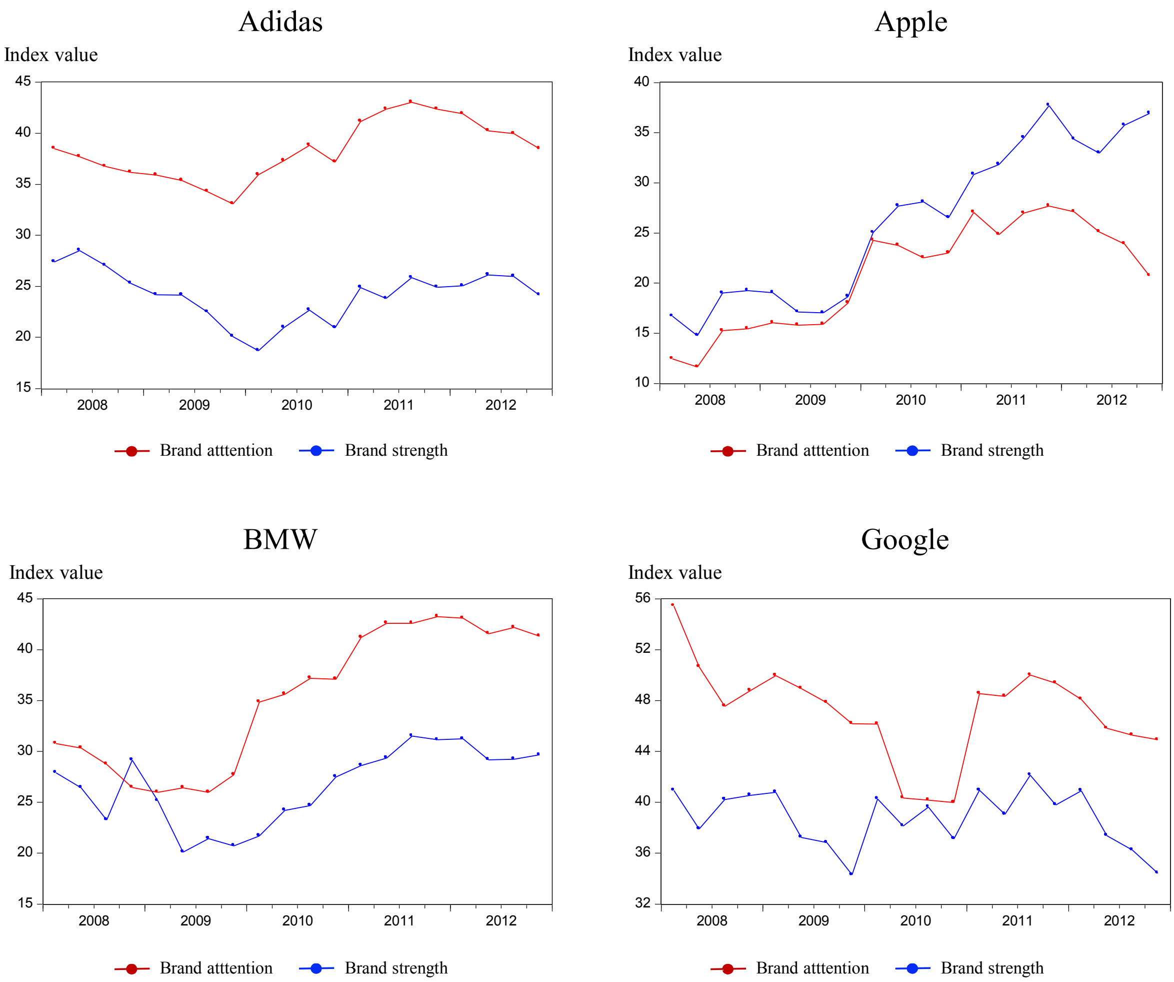
Appendix C: Reflective and Sticky Brand Metric Structure

Table C1
ANALYSIS OF BRAND METRIC STICKINESS

Model: $X_t = a + bX_{t-1} + e$			Brand attention	Brand strength
Data frequency	# of brands	N	R^2	R^2
Weekly	577	94,062	.910	.986
Quarterly	522	6,942	.950	.990
Annual	394	1,507	.806	.922
			Harris Equitrend	
Annual	436	1,669	.813	

Notes:
1. We include Harris' Equitrend, for which we have data in another dataset available, for comparison purposes. The Equitrend measure has been widely used in academic research to measure customer-based brand equity (e.g., Rego, Billet, and Morgan 2009; Bharadwaj, Tuli, and Bonfrer 2011). It is only available at the annual level.
2. The number of brands for the YouGov metrics differ across the temporal aggregation level due to missing information. The analysis requires at least 3 succeeding periods. This is not the case for 54 brands on the quarterly basis and 183 brands on yearly basis.

Figure C1
EXAMPLES OF EVOLUTION AND VARIATION IN BRAND METRICS



Note: Figures display evolution and variation in brand metrics based on quarterly aggregation of data.

Appendix D: Collection of Crisis Event Data

Our data collection process involved a systematic 5-step approach:

1. In the first step we generated crisis keywords commonly used in news headlines and articles with regard to the different crisis events. For this purpose, we conducted three 30-minute brainstorming sessions with a panel of 4-5 CSI experts and journalists for each crisis type (12 sessions in total). Additionally, we expanded and cross-checked the keyword list through the Google AdWords "Find related searches" function.
2. We then pre-tested the keywords (up to 60 keywords per crisis type) on a random sample of ten a priori identified events in order to reduce complexity and efficiency within the search algorithm. Based on the hit ratio of relevant articles and the total number of generated hits we excluded about 50% of all keywords.
3. Next, we conducted search queries in LexisNexis and additional news archives by connecting all brands available from the YouGov database with our keyword list and searched for hits within the headlines and lead paragraphs of articles (Example LexisNexis: HLEAD("BRAND X") AND ("KEYWORD Y_1" OR "KEYWORD Y_2" OR "KEYWORD Y_3" OR…).
4. In a fourth step, three coders (one co-author) individually read all relevant articles and categorized crisis events with regard to crisis type, immediate firm reaction mentioned in media articles, crisis origin, and further crisis-related information. Coding agreement across all variables was greater than 90%. Cases of non-agreement were decided by discussion.
5. Finally, in addition to the original crisis search, we checked for possible confounding events for all detected crisis events within the detected media articles, company reports, and news published through corporate webpages.

Appendix E: Representativeness and Exogeneity of Events

Table E1 lists the crisis events that are part of our empirical analysis. It shows the brand name, the crisis type, and when the crisis event was first published.

Table E2 compares the 69 brands of our model analysis that experienced a well-publicized crisis event during our observation period with the brands of the YouGov brand universe. We compare the brand crisis sample with the YouGov universe along brand metrics, advertising expenditures and industry membership. Due to missing information on advertising expenditures and consecutive years, the YouGov universe includes 378 brands. The t-test on mean differences suggest that our crisis sample is not systematically different from the YouGov brand universe.

In addition, we show the percentage of new brands with a crisis event from one year to the next year. On average, 61% brands are new. This also suggests are random process or at least a process that is not driven by the past.

Finally, we set up a logit model to explain the occurrence of a crisis event based on a brand's history of crisis events and past values for our focal brand metrics, their industry averages, advertising expenditures, and firm size. This analysis can be considered a "Granger-like" causality test. It is not a strict Granger causality test since our dependent variable is non-metric. However, the model follows the spirit of the test and the definition of Granger causality. Results in Table E4 show that past values of our focal endogenous metrics brand attention and brand strength cannot explain the occurrence of a crisis event in addition to past occurrences of a crisis event. Hence, we find no evidence to reject our assumption that the crisis events are truly exogenous.

Table E1
CRISIS EVENTS INCLUDED IN EMPIRICAL ANALYSIS

Year	Week	Brand	Crisis type
2008	14	Adidas	Human rights / working conditions violation
2008	8	Aldi	Product-harm crisis
2008	16	Aldi	Human rights / working conditions violation
2008	33	Aldi	Fair operating practices violation
2008	14	British Airways	Product-harm crisis
2008	21	Burger King	Human rights / working conditions violation
2008	36	Deutsche Bahn	Fair operating practices violation
2008	14	Deutsche Bank	Product-harm crisis
2008	19	Deutsche Bank	Product-harm crisis
2008	25	Deutsche Bank	Product-harm crisis
2008	44	Deutsche Bank	Product-harm crisis
2008	52	Deutsche Bank	Product-harm crisis
2008	9	Deutsche Post	Human rights / working conditions violation
2008	15	Deutsche Telekom	Product-harm crisis
2008	22	Deutsche Telekom	Human rights / working conditions violation
2008	41	Deutsche Telekom	Human rights / working conditions violation
2008	24	e.on	Fair operating practices violation
2008	52	EnBW	Fair operating practices violation
2008	36	Google	Product-harm crisis
2008	26	IKEA	Product-harm crisis
2008	28	L'Oreal	Fair operating practices violation
2008	37	Lidl	Human rights / working conditions violation
2008	48	Lidl	Human rights / working conditions violation
2008	9	Microsoft	Fair operating practices violation
2008	51	Microsoft	Product-harm crisis
2008	8	Nokia	Human rights / working conditions violation
2008	8	Porsche	Product-harm crisis
2008	17	Puma	Human rights / working conditions violation
2008	12	Reebok	Fair operating practices violation
2008	17	T-Mobile	Fair operating practices violation
2008	52	Toyota	Product-harm crisis
2008	17	Vodafone	Fair operating practices violation
…continued			
2010	3	Microsoft	Product-harm crisis
2010	11	Microsoft	Product-harm crisis
2010	30	Microsoft	Product-harm crisis
2010	45	Microsoft	Product-harm crisis
2010	2	Postbank	Product-harm crisis
2010	3	Rewe	Fair operating practices violation
2010	2	Sparkasse	Product-harm crisis
2010	5	Toyota	Product-harm crisis
2010	16	Toyota	Product-harm crisis
2010	26	Toyota	Product-harm crisis
2010	35	Toyota	Product-harm crisis
2010	43	Toyota	Product-harm crisis
2010	25	Volkswagen	Product-harm crisis
2010	51	Volkswagen	Product-harm crisis
2011	16	Adidas	Fair operating practices violation
2011	33	Aldi	Product-harm crisis
2011	12	Apple	Human rights / working conditions violation
2011	22	Apple	Human rights / working conditions violation
2011	22	Aral	Fair operating practices violation
2011	42	BlackBerry	Product-harm crisis
2011	36	BMW	Product-harm crisis
2011	45	BMW	Product-harm crisis
2011	31	Danone	Fair operating practices violation
2011	14	Deutsche Bahn	Fair operating practices violation
2011	18	Deutsche Bahn	Product-harm crisis
2011	21	Deutsche Bahn	Product-harm crisis
2011	7	Deutsche Bank	Product-harm crisis
2011	13	Deutsche Bank	Product-harm crisis
2011	19	Deutsche Bank	Product-harm crisis
2011	32	Deutsche Bank	Product-harm crisis
2011	31	Deutsche Telekom	Fair operating practices violation
2011	20	Facebook	Product-harm crisis

Year	Week	Band	Crisis type	…continued			
2008	15	Volkswagen	Product-harm crisis	2011	47	Facebook	Product-harm crisis
2008	28	Volkswagen	Fair operating practices violation	2011	9	Google	Fair operating practices violation
2009	12	Actimel	Fair operating practices violation	2011	23	Google	Product-harm crisis
2009	6	Aldi	Human rights / working conditions violation	2011	26	Google	Fair operating practices violation
2009	14	BP	Environmental Scandal	2011	35	H & M	Human rights / working conditions violation
2009	6	Deutsche Bahn	Fair operating practices violation	2011	41	HTC	Product-harm crisis
2009	28	Deutsche Bank	Fair operating practices violation	2011	41	IKEA	Product-harm crisis
2009	25	Deutsche Post	Fair operating practices violation	2011	6	Intel	Product-harm crisis
2009	36	Deutsche Telekom	Fair operating practices violation	2011	53	Lidl	Human rights / working conditions violation
2009	47	Deutsche Telekom	Human rights / working conditions violation	2011	12	Netto	Human rights / working conditions violation
2009	18	Edeka	Fair operating practices violation	2011	47	Nutella	Fair operating practices violation
2009	12	EnBW	Human rights / working conditions violation	2011	51	Opel	Product-harm crisis
2009	42	Ford	Product-harm crisis	2011	34	Porsche	Product-harm crisis
2009	6	Google	Product-harm crisis	2011	35	Puma	Environmental Scandal
2009	52	IKEA	Product-harm crisis	2011	2	Renault	Human rights / working conditions violation
2009	20	Intel	Fair operating practices violation	2011	33	Shell	Environmental Scandal
2009	51	Intel	Fair operating practices violation	2011	18	Sony	Fair operating practices violation
2009	14	Lidl	Human rights / working conditions violation	2011	21	Sony	Product-harm crisis
2009	44	Lidl	Human rights / working conditions violation	2011	21	Starbucks	Human rights / working conditions violation
2009	3	Lufthansa	Human rights / working conditions violation	2011	5	Toyota	Product-harm crisis
2009	17	Lufthansa	Fair operating practices violation	2011	9	Toyota	Product-harm crisis
2009	40	Lufthansa	Product-harm crisis	2011	23	Toyota	Product-harm crisis
2009	20	Metro	Human rights / working conditions violation	2011	25	United Airlines	Product-harm crisis
2009	15	Microsoft	Fair operating practices violation	2011	10	Volkswagen	Product-harm crisis
2009	29	Microsoft	Product-harm crisis	2011	35	Volkswagen	Product-harm crisis
2009	6	Nokia	Human rights / working conditions violation	2011	36	Wiesenhof	Environmental Scandal
2009	46	Nokia	Product-harm crisis	2011	34	Zara	Human rights / working conditions violation
2009	17	Opel	Product-harm crisis	2012	18	Aldi	Human rights / working conditions violation

Year	Week	Band	Crisis type	…continued			
2009	16	Philips	Product-harm crisis	2012	21	Aldi	Product-harm crisis
2009	44	Postbank	Fair operating practices violation	2012	27	Aldi	Product-harm crisis
2009	44	Real	Product-harm crisis	2012	40	Aldi	Product-harm crisis
2009	22	Shell	Human rights / working conditions violation	2012	12	Apple	Product-harm crisis
2009	27	Sparkasse	Fair operating practices violation	2012	15	Apple	Fair operating practices violation
2009	47	T-Mobile	Fair operating practices violation	2012	38	Apple	Product-harm crisis
2009	52	Tchibo	Fair operating practices violation	2012	42	Apple	Human rights / working conditions violation
2009	5	Toyota	Product-harm crisis	2012	46	Apple	Human rights / working conditions violation
2009	40	Toyota	Product-harm crisis	2012	38	BlackBerry	Product-harm crisis
2009	16	Vattenfall	Fair operating practices violation	2012	13	BMW	Product-harm crisis
2009	36	vodafone	Fair operating practices violation	2012	48	C & A	Human rights / working conditions violation
2010	34	Adidas	Human rights / working conditions violation	2012	43	Commerzbank	Product-harm crisis
2010	34	Aldi	Human rights / working conditions violation	2012	24	Deutsche Bahn	Fair operating practices violation
2010	22	Apple	Human rights / working conditions violation	2012	7	Deutsche Bank	Product-harm crisis
2010	26	Apple	Product-harm crisis	2012	19	Deutsche Bank	Product-harm crisis
2010	12	Aral	Fair operating practices violation	2012	50	Deutsche Bank	Fair operating practices violation
2010	40	BMW	Product-harm crisis	2012	45	Deutsche Post	Fair operating practices violation
2010	44	BMW	Product-harm crisis	2012	10	Facebook	Product-harm crisis
2010	17	BP	Environmental Scandal	2012	2	Ford	Product-harm crisis
2010	5	Citroen	Product-harm crisis	2012	36	Gazprom	Fair operating practices violation
2010	48	Coca-Cola	Product-harm crisis	2012	18	Google	Fair operating practices violation
2010	2	Commerzbank	Product-harm crisis	2012	31	Haribo	Fair operating practices violation
2010	18	Deutsche Bank	Fair operating practices violation	2012	18	IKEA	Human rights / working conditions violation
2010	52	Deutsche Bank	Fair operating practices violation	2012	40	IKEA	Human rights / working conditions violation
2010	3	Edeka	Fair operating practices violation	2012	2	KiK	Human rights / working conditions violation
2010	15	Facebook	Product-harm crisis	2012	40	Lufthansa	Product-harm crisis
2010	19	Facebook	Fair operating practices violation	2012	21	Microsoft	Product-harm crisis
2010	22	Facebook	Fair operating practices violation	2012	29	Microsoft	Fair operating practices violation
2010	31	Facebook	Product-harm crisis	2012	38	Microsoft	Product-harm crisis
2010	43	Facebook	Human rights / working conditions violation	2012	44	O2	Fair operating practices violation

Year	Week	Band	Crisis type
2010	51	Ford	Fair operating practices violation
2010	3	Google	Fair operating practices violation
2010	21	Google	Human rights / working conditions violation
2010	30	KiK	Human rights / working conditions violation
2010	6	Lexus	Product-harm crisis
2010	16	Lexus	Product-harm crisis
2010	21	Lexus	Product-harm crisis
2010	26	Lexus	Product-harm crisis
2010	4	Lidl	Product-harm crisis
2010	15	Lidl	Human rights / working conditions violation
2010	45	Lidl	Product-harm crisis
2010	23	McDonald's	Product-harm crisis
2010	38	Mercedes-Benz	Fair operating practices violation
2010	42	Mercedes-Benz	Product-harm crisis
2010	3	Metro	Fair operating practices violation
2010	19	Metro	Human rights / working conditions violation
2010	34	Metro	Human rights / working conditions violation
…continued			
2012	8	Porsche	Product-harm crisis
2012	47	Renault	Product-harm crisis
2012	37	Ryanair	Product-harm crisis
2012	50	Ryanair	Product-harm crisis
2012	32	Samsung	Human rights / working conditions violation
2012	9	Sparkasse	Fair operating practices violation
2012	13	Total	Environmental Scandal
2012	10	Toyota	Product-harm crisis
2012	31	Toyota	Product-harm crisis
2012	41	Toyota	Product-harm crisis
2012	46	Toyota	Product-harm crisis
2012	10	Vattenfall	Environmental Scandal
2012	44	vodafone	Product-harm crisis
2012	3	Volkswagen	Product-harm crisis
2012	45	Volkswagen	Product-harm crisis
2012	10	Wiesenhof	Environmental Scandal
2012	17	Wiesenhof	Fair operating practices violation

Table E2
EXTERNAL VALIDITY OF CRISIS SAMPLE

	YouGov brand universe	**Crisis sample**	T-test of differences between means
	N = 378	N = 69	p-value
	Mean	Mean	
Brand attention	14.09	23.01	.000
Brand strength	9.21	12.26	.159
Advertising expenditures ($)	908,549	1,112,429	.321
Industry			
Food, Beverage & Tobacco	20%	9%	.027
Telecommunication Services	4%	4%	.870
Transportation	7%	9%	.652
Software & Services	4%	4%	.870
Consumer Services	6%	4%	.491
Consumer Durables & Apparel	13%	22%	.058
Household & Personal Products	6%	2%	.108
Automobiles & Components	10%	15%	.288
Retailing	10%	9%	.747
Utilities	7%	6%	.817
Food & Staples Retailing	7%	10%	.368
Financials	5%	6%	.717

Table E3
PERCENTAGE OF NEW BRANDS WITH CRISIS IN SUCCEEDING YEAR

Mean	2008-2009	2009-2010	2010-2011	2011-2012
61%	55%	52%	70%	67%

Table E4
LOGIT REGRESSION RESULTS FOR TESTING THE EXOGENEITY ASSUMPTION OF CRISIS EVENTS –

Dependent variable: Crisis event (Yes=1/No=0)	Weekly aggregation		Quarterly aggregation		Annual aggregation	
Independent variables	Estimated coefficient	Std. Error	Estimated coefficient	Std. Error	Estimated coefficient	Std. Error
Constant	-2.408	.130 ***	-2.503	.382 ***	-1.086	.686
Lagged brand attention[1)]	.005	.003	.015	.010	.010	.021
Lagged brand strength[1)]	-.001	.002	.005	.006	-.002	.011
Lagged industry brand attention[1)]	-.029	.012	-.060	.036	-.018	.043
Lagged industry brand strength[1)]	.010	.008	.024	.024	-.031	.066
Lagged ad expenditures[1)]	6.8×10^{-9}	2.2×10^{-8}	2.7×10^{-8}	6.8×10^{-8}	4.4×10^{-8}	1.32×10^{-7}
Lagged number of events[2)]	.112	.011 ***	.248	.028 ***	.252	.065 ***
Firm size	1.7×10^{-7}	2.3×10^{-7}	2.0×10^{-7}	7.1×10^{-7}	6.6×10^{-7}	1.3×10^{-6}
Log Likelihood		-1041.78		-460.69		-135.79
N		16,328		1,230		223

Notes: ** $p < .05$, *** $p < .01$ (two-sided).
[1)] Variables are measured as the average index/ad expenditures value in the 4 weeks prior to the crisis event (weekly aggregation), as the average in the preceding quarter (quarterly aggregation) and the preceding year (annual aggregation).
[2)] Prior number of events is the sum of crisis events within our sample that the respective brand was exposed to prior to the respective crisis event.

Appendix F: Model Free Evidence

Table F1
MODEL FREE EVIDENCE: SIMPLE DIFFERENCES IN BRAND METRICS

	Brand attention							*Brand strength*						
1-week (before and after event)						Difference tests							Difference tests	
	Mean	Median	SD	Min	Max	t-test	F-test	Mean	Median	SD	Min	Max	t-value	F-test
Total	4.53%	2.29%	.116	-27.1%	81.0%	5.31***		-2.08%	-1.51%	.044	-24.2%	7.58%	-5.96***	
Comparison of product-harm with (average) CSI event														
Product-harm event	3.75%	1.42%	.117	-27.1%	81.0%	3.04***	$F_{1,186}$ = .78	-1.29%	-.79%	.038	-19.8%	7.58%	-3.20***	$F_{1,186}$ = 4.02
CSI event	5.26%	3.02%	.115	-11.8%	52.8%	4.60***	p = .377	-2.60%	-1.67%	.050	-24.2%	6.12%	-5.11***	p = .046
Comparison of all four types of events														
Product-harm event	3.75%	1.42%	.117	-27.1%	81.0%	3.04***		-1.29%	-.79%	.038	-19.8%	7.58%	-3.20***	
Violation of fair operating practices	4.36%	3.73%	.073	-11.6%	25.6%	4.02***	$F_{1,185}$ = 1.66	-1.15%	-1.30%	.037	-15.2%	6.12%	-4.52***	$F_{1,186}$ = 6.10
Violation of human rights / working conditions	4.83%	1.40%	.138	-11.8%	52.8%	2.27**	p = .178	-3.44%	-2.42%	.049	-17.2%	4.36%	-2.10**	p = .001
Environmental scandal	13.85%	9.00%	.146	-.93%	38.9%	2.30*		-6.98%	-4.31%	.078	-24.2%	.98%	-2.19*	
2-week (before and after event)						Difference tests							Difference tests	
	Mean	Median	SD	Min	Max	t-test	F-test	Mean	Median	SD	Min	Max	t-test	F-test
Total	3.57%	1.49%	.103	-18.6%	73.5%	4.70***		-1.69%	-1.11%	.040	-21.9%	7.63%	-5.96***	
Comparison of product-harm with (average) CSI event														
Product-harm event	3.75%	1.66%	.103	-15.5%	73.5%	2.77***	$F_{1,183}$ = .481	-.80%	-.66%	.035	-21.9%	7.63%	-3.20***	$F_{1,183}$ = 5.54
CSI event	4.08%	1.43%	.103	-18.6%	43.0%	3.84***	p = .489	-2.18%	-1.60%	.043	-17.7%	4.86%	-5.11***	p = .020
Comparison of all four types of events														
Product-harm event	3.75%	1.66%	.103	-15.5%	73.5%	2.77***		-.80%	-.66%	.035	-21.9%	7.63%	-3.20***	
Violation of fair operating practices	2.55%	1.26%	.066	-11.1%	22.3%	2.60**	$F_{1,183}$ = 3.27	-.84%	-.65%	.033	-14.9%	4.86%	-4.52***	$F_{1,183}$ = 7.28
Violation of human rights / working conditions	3.93%	1.68%	.111	-18.6%	36.8%	2.26**	p = .022	-2.94%	-2.20%	.042	-14.92%	3.97%	-2.10**	p = .000
Environmental scandal	15.09%	11.27%	.166	-1.75%	43.0%	2.23*		-6.43%	-6.50%	.061	-17.66%	2.51%	-2.19**	

Notes: * p < .1, ** p < .05, *** p < .01 (two-sided). Results are based on percentage changes of the transformed YouGov Brand metrics.

Appendix G: Robustness of Brand Performance Model

Appendix G contains several robustness checks. Table G1 and G2 present the results of a Panel ECM specification. In the first model, we specify two crisis dummies for product-harm and CSI events whose parameters are assumed to be normally distributed across brands. We estimate their mean and variance by applying simulated maximum likelihood. The second model includes four dummies for the four crisis types. We impose the same heterogeneity assumptions on their parameters. In all Panel ECM specifications, we also assume and estimate parameter heterogeneity for the intercept, advertising expenditures, industry averages of brand attention and brand strength, and the adjustment parameter.

Table G3 shows model estimations with additional moderator variables. Table G4 presents results of ECM when we use media coverage instead of our crisis event dummy variables. Technically, we estimate the interaction of media coverage with the crisis event. Results are fully consistent with our focal model results.

Tables G5 and G6 include model estimations with selected brand items as dependent variable. Specifically, we consider the brand recommendation items and the average of brand value and brand quality items. Results are again consistent with our focal model results.

Finally, we check our assumption on the media threshold, i.e. a crisis event is only included in our analysis if at least three out of the 15 leading media outlets report on it. Table G7 shows that there are no crisis event effects for those events that do not pass the threshold. The outcome is the same if we just consider media coverage = 2. Table G8 reestimates our focal model by including all crisis events. Results are consistent with our focal model results but tend to be a bit weaker due to the inclusion of not well-publicized events.

Table G1

RESULTS FOR PANEL ERROR-CORRECTION-MODEL INCLUDING DUMMIES FOR PRODUCT-HARM AND CSI CRISIS EVENTS

		Brand attention				Brand strength			
		Expected sign	*Estimated coefficient*		*T-value for difference to product-harm effect*	*Expected sign*	*Estimated coefficient*		*T-value for difference to product-harm effect*
Intercept		+/-	.0895 ***	(.0028)		+/-	.0009	(.0012)	
Advertising expenditures									
	Immediate	+	.0021 **	(.0010)		+	-.0008	(.0006)	
	Cumulative	+	.0056 ***	(.0006)		+	.0185 ***	(.0008)	
Industry brand strength									
	Immediate					+	.0570 ***	(.0020)	
	Cumulative					+	.0235 ***	(.0003)	
Industry brand attention									
	Immediate	+	.0439 ***	(.0018)					
	Cumulative	+	.0187 ***	(.0005)					
Crisis event									
Product-harm crisis	*Immediate*	+	.0207 ***	(.0040)		-	-.0142 ***	(.0037)	
	Cumulative	+	.1689 ***	(.0210)		-	-.1286 ***	(.0345)	
CSI crisis	*Immediate*	+	.0351 ***	(.0054)	2.14**	-	-.0322 ***	(.0033)	-3.65***
	Cumulative	+	.1787 ***	(.0219)	.32	-	-.2875 ***	(.0310)	-3.43***
Adjustment		-1< g <0	-.3406 ***	(.0032)		-1< g <0	-.1379 ***	(.0022)	
Long-term Trend		no	-.0060 ***	(.0021)		no	.0005	(.0024)	

Notes: * p < .1,** p < .05, *** p < .01 (two-sided). Standard errors in parentheses.
We accounted for brand heterogeneity by estimating random coefficients for the constant, advertising expenditures, industry brand strength, industry brand attention, the adjustment parameter, and all crisis event variables. We do not report estimated variances of parameters. They may be obtained upon request.

Table G2
RESULTS FOR PANEL ERROR-CORRECTION-MODEL: ALL FOUR CRISIS TYPES

		Brand attention				*Brand strength*			
		Expected sign	*Estimated coefficient*		*T-value for difference to product-harm effect*	*Expected sign*	*Estimated coefficient*		*T-value for difference to product-harm effect*
Intercept		+/-	.0915 ***	(.0030)		+/-	.0105 ***	(.0010)	
Advertising expenditures									
	Immediate	+	.0008	(.0010)		+	.0038 ***	(.0006)	
	Cumulative	+	.0039 ***	(.0006)		+	.0092 ***	(.0010)	
Industry brand strength									
	Immediate					+	.0571 ***	(.0023)	
	Cumulative					+	.0137 ***	(.0005)	
Industry brand attention									
	Immediate	+	.0430 ***	(.0020)					
	Cumulative	+	.0144 ***	(.0006)					
Crisis event									
Product-harm crisis	*Immediate*	+	.0173 ***	(.0047)		-	-.0166 ***	(.0035)	
	Cumulative	+	.1177 ***	(.0225)		-	-.1806 ***	(.0414)	
Violation of fair operating practice	*Immediate*	+	.0366 ***	(.0070)	2.30**	-	-.0204 ***	(.0055)	-.59
	Cumulative	+	.1783 ***	(.0328)	1.53	-	-.1946 **	(.0781)	-.16
Violation of human rights / working conditions	*Immediate*	+	.0362 ***	(.0097)	1.75	-	-.0393 ***	(.0062)	-3.20***
	Cumulative	+	.2028 ***	(.0415)	1.80*	-	-.4109 ***	(.0887)	-2.35***
Environmental scandal	*Immediate*	+	.0338	(.0287)	.57	-	-.0496 ***	(.0103)	-3.03***
	Cumulative	+	.1661 **	(.0851)	.55	-	-1.145 ***	(.1039)	-8.66***
Adjustment		-1< g <0	-.3510 ***	(.0050)		-1< g <0	-.1120 ***	(.0023)	
Long-term Trend		no	-.0045 *	(.0024)		no	.0208 ***	(.0007)	

Notes: * p < .1,** p < .05, *** p < .01 (two-sided). Standard errors in parentheses.
We accounted for brand heterogeneity by estimating random coefficients for the constant, advertising expenditures, industry brand strength, industry brand attention, the adjustment parameter, and all crisis event variables. We do not report estimated variances of parameters. They may be obtained upon request.

Table G3

WLS ESTIMATION RESULTS OF BRAND EFFECTS DRIVERS (EXTENDED MODEL)

Dependent variable:			*Brand attention*					*Brand strength*			
			Estimated immediate effect		*Estimated cumulative effect*			*Estimated immediate effect*		*Estimated cumulative effect*	
		Exp. sign	*Coefficient*		*Coefficient*		*Exp. sign*	*Coefficient*		*Coefficient*	
Intercept		+/-	-.138	(.150)	-1.10*	(.648)	+/-	-.015	(.053)	-.259	(.300)
Crisis type	*Product-harm crisis (base)*		-	-	-	-		-	-	-	
	CSI (average)	+/-	.031	(.038)	-.026	(.189)	-	-.077***	(.011)	-.250***	(.116)
	Violation of fair operating practice		.022	(.047)	-.405***	(.152)	+/-	-.038 ***	(.015)	-.068	(.076)
	Human rights / working violation	+/-	.011**	(.047)	.390**	(.153)	+/-	-.158 ***	(.013)	-.144*	(.087)
	Environmental scandal	+/-	-.040	(.085)	-.062	(.363)	+/-	-.035 **	(.018)	-.540***	(.154)
	Product-harm and CSI crisis	+/-	-.054	(.050)	-.319*	(.170)	+/-	-.014	(.014)	.033	(.083)
<u>*Crisis characteristics*</u>											
Media coverage		+	.030***	(.004)	.094***	(.014)	-	-.006***	(.001)	-.035***	(.008)
Crisis origin	*International (base)*		-	-	-	-		-	-	-	-
	National	+/-	.028	(.033)	.075	(.118)	-	-.051***	(.012)	-.087**	(.052)
Immediate firm reaction	*No reaction (base)*		-	-	-	-		-	-	-	-
	Deny responsibility	+/-	-.062	(.040)	.352**	(.141)	+/-	.004	(.010)	-.153**	(.072)
	Accept responsibility	+/-	-.050*	(.029)	.037	(.118)	+/-	.063***	(.011)	.048	(.053)
	Change of reaction over time	+/-	-	-	.107	(.173)	+/-	-	-	-.007	(.008)
Objectivity of claim	*Accusation (base)*		-	-	-	-		-	-	-	-
	Fact	+/-	-.025	(.034)	.086	(.114)	-	-.051***	(.010)	-.020	(.058)
Responsibility	*Single actor (base)*	-	-	-	-	-		-	-	-	-
	Corporate action	+/-	.025	(.082)	.082	(.307)	-	-.031*	(.021)	-.032	(.113)
<u>*Brand & firm characteristics*</u>											
Product type	*Durables (base)*	-	-	-	-	-		-	-	-	-
	Non-Durables	+/-	.026	(.064)	-.040	(.216)	+/-	.059**	(.026)	.214	(.151)
	Retail	+/-	.069*	(.036)	.334***	(.128)	+/-	-.020**	(.011)	.034	(.071)
	Services	+/-	.064	(.044)	-.302*	(.170)	+/-	-.010	(.015)	.244**	(.095)
Prior brand strength		-	-.001*	(.001)	-.011***	(.003)	+	$4.3x10^{-4}$*	($2.7x10^{-4}$)	.004***	(.002)
Firm size		-	-.002	(.010)	-.049	(.048)	+/-	.011***	(.003)	.034*	(.020)
Crisis history		+/-	-.003	(.004)	-.022*	(.016)	-	.002	(.001)	-.023***	(.008)
R2			*.580*		*.320*			*.737*		*.310*	
N			*214*		*214*			*214*		*214*	

Notes: * p<.1, ** p<.05, *** p<.01. Tests are one-sided if clear directional effects are expected, two-sided if not. Standard errors in parentheses.

1) The coefficient for CSI (average) is the mean of the estimated coefficients for the three CSI-crisis types. The standard error is calculated from the associated variance-covariance matrix. We also estimated a model that includes a dummy variable for CSI event only (instead of three different types). Results are fully consistent with this table.

Table G4
2SLS ESTIMATION RESULTS (ECM) WITH MEDIA COVERAGE AS CRISIS VARIABLE

		Brand attention			*Brand strength*		
	Obs	*Exp. sign*	*Estimated average coefficient*	*Z-Score*	*Exp. sign*	*Estimated average coefficient*	*Z-Score*
Intercept	69	+/-	-.1058	-3.16 ***	+/-	.0141	2.83 ***
Advertising expenditures							
Immediate	69	+	.0080	5.45 ***	+	.0003	.02
Cumulative	69	+	.0268	9.74 ***	+	.0017	2.78 ***
Industry brand strength							
Immediate	69		-	-	+	.0362	27.45 ***
Cumulative	69		-	-	+	.0254	29.00 ***
Industry brand attention							
Immediate	69	+	.0608	28.23 ***		-	-
Cumulative	69	+	.0332	21.27 ***		-	-
Media coverage (in crisis event)							
Immediate	69	+	.0044	8.58 ***	-	-.0025	-18.39 ***
Cumulative	69	+	.0125	10.89 ***	-	-.0101	-16.99 ***
Adjustment	69	-1< g <0	-.5544	-34.88 ***	-1< g <0	-.3944	-47.80 ***
Long-term Trend	69	no	-.1133	-15.08 ***	no	.0016	.08

Note: ** p < .05, *** p < .01 (two-sided).

Table G5.1
2SLS ESTIMATION RESULTS FOR BRAND RECOMMENDATION

			Brand recommendation	
	Obs	*Exp. sign*	*Estimated average coefficient*	*Z-Score*
Intercept	69	+/-	.0286	3.12 ***
Advertising expenditures				
Immediate	69	+	.0022	1.58 *
Cumulative	69	+	.0025	.90
Industry brand recommendation				
Immediate	69	+	.0303	16.96 ***
Cumulative	69	+	.0245	20.66 ***
Crisis event				
Immediate	214	-	-.0036	-3.01 ***
Cumulative	214	-	-.0407	-11.58 ***
Adjustment	69	-1< g <0	-.7253	-71.37 ***
Long-term Trend	69	no	-.0169	-5.44 ***

Note: * p < .1, ** p < .05, *** p < .01 (two-sided).

Table G5.2
WLS ESTIMATION RESULTS OF BRAND RECOMMENDATION

Dependent variable:			*Brand recommendation*			
			Estimated immediate effect		*Estimated cumulative effect*	
		Exp.	*Coefficient*		*Coefficient*	
Intercept		+/-	.048	(.104)	.100	(.191)
Crisis type	*PHC (base)*		-	-	-	-
	CSI (average)	+/-	-.062 **	(.001)	-.153 ***	(.001)
	Violation of FOP	+/-	.101 ***	(.027)	.054	(.052)
	Violation of HRWC	+/-	-.005	(.027)	-.095 *	(.049)
	Environm. scandal	+/-	-.145 ***	(.049)	-.210 **	(.095)
	Both types	+/-	.187 ***	(.029)	.335 ***	(.062)
<u>*Crisis characteristics*</u>						
Media coverage		-	-.010 ***	(.004)	-.039 ***	(.006)
Crisis origin	*International (base)*		-	-	-	-
	National	-	-.091 ***	(.022)	-.198 ***	(.043)
Immediate firm reaction	*No reaction (base)*		-	-	-	-
	Deny responsibility	+/-	-.105 ***	(.024)	-.140 ***	(.047)
	Accept responsibility	+/-	.075 ***	(.021)	-.004	(.041)
<u>*Brand & firm characteristics*</u>						
Product type	*Retail (base)*	-	-	-	-	-
	Non-Durables	+/-	.039	(.033)	.056	(.089)
	Durables	+/-	-.044 *	(.024)	-.097 **	(.047)
	Services	+/-	-.125 ***	(.036)	.047	(.065)
Prior brand strength		+	-.002 ***	(.001)	.004 ***	(.001)
Firm size		+/-	.010	(.008)	.014	(.015)
Crisis history		-	-.004	(.003)	.003	(.006)
$\mathbf{R^2}$			*.440*		*.377*	
N			*214*		*214*	

Notes: * p<.1, ** p<.05, *** p<.01 (two-sided). Standard errors in parentheses. PHC = Product-harm crisis, CSI = Corporate social irresponsibility crisis, FOP = Fair operating practices, HRW = Human rights / Working conditions.

[1] The coefficient for CSI (average) is the mean of the estimated coefficients for the three CSI-crisis types. The standard error is calculated from the associated variance-covariance matrix. We also estimated a model that includes a dummy variable for CSI event only (instead of three different types). Results are fully consistent with this table.

Table G6.1
2SLS ESTIMATION RESULTS FOR BRAND VALUE/QUALITY[1)]

			Brand value/quality	
	Obs	*Exp. sign*	*Estimated average coefficient*	*Z-Score*
Intercept	69	+/-	.0119	1.97 **
Advertising expenditures				
Immediate	69	+	.0006	.40
Cumulative	69	+	.0025	4.04 ***
Industry brand value/quality				
Immediate	69	+	.0317	20.74 ***
Cumulative	69	+	.0254	24.73 ***
Crisis event				
Immediate	214	-	-.0173	-17.43 ***
Cumulative	214	-	-.0416	-13.55 ***
Adjustment	69	-1< g <0	-.5712	-62.90 ***
Long-term Trend	69	no	.0043	1.69 **

Notes: * p < .1, ** p < .05, *** p < .01 (two-sided).
[1)] Brand value/quality is a combined measure from the YouGov items brand value and brand quality and present items as they are closely associated with product-related brand dimensions.

Table G6.2
WLS ESTIMATION RESULTS OF BRAND VALUE/QUALITY[1)]

			Brand value/quality			
	Dependent variable:		*Estimated immediate effect*		*Estimated cumulative effect*	
		Exp.	*Coefficient*		*Coefficient*	
Intercept		+/-	-.045	(.069)	.064	(.219)
Crisis type	*PHC (base)*		-	-	-	-
	CSI (average)[2)]	+/-	-.029 *	(.017)	-.096	(.090)
	Violation of FOP	+/-	.006	(.017)	.115 **	(.055)
	HRW violation	+/-	-.088 ***	(.016)	-.164 ***	(.051)
	Environm. scandal	+/-	-.007	(.036)	-.240 ***	(.091)
	Both types	+/-	.058 **	(.023)	.193 ***	(.063)
Crisis characteristics						
Media coverage		-	-.007 ***	(.002)	-.032 ***	(.006)
Crisis origin	*International (base)*		-	-	-	-
	National	-	-.102 ***	(.015)	-.224 ***	(.042)
Immediate firm reaction	*No reaction (base)*		-	-	-	-
	Deny responsibility	+/-	-.034 **	(.017)	-.189 ***	(.052)
	Accept responsibility	+/-	.027 **	(.012)	.011	(.044)
Brand & firm characteristics						
Product type	*Retail (base)*	-	-	-	-	-
	Non-Durables	+/-	.020	(.026)	.045	(.078)
	Durables	+/-	-.002	(.015)	.030	(.046)
	Services	+/-	$4.6x10^{-5}$	(.020)	.071	(.056)
Prior brand strength		+	$-9.4x10^{-4}$ ***	($3.7x10^{-4}$)	$6.5x10^{-4}$	(.001)
Firm size		+/-	.012 **	(.005)	.011	(.016)
Crisis history		-	-.001	(.002)	-.005	(.006
R^2			*.479*		*.399*	
N			*214*		*214*	

Notes: * p<.1, ** p<.05, *** p<.01 (two-sided). Standard errors in parentheses. PHC = Product-harm crisis, CSI = Corporate social irresponsibility crisis, FOP = Fair operating practices, HRW = Human rights / Working conditions.
[1)] Brand value/quality is a combined measure from the YouGov items brand value and brand quality and present items as they are closely associated with product-related brand dimensions.
[2)]The coefficient for CSI (average) is the mean of the estimated coefficients for the three CSI-crisis types. The standard error is calculated from the associated variance-covariance matrix. We also estimated a model that includes a dummy variable for CSI event only (instead of three different types). Results are fully consistent with this table.

Table G7

2SLS ESTIMATION RESULTS FOR ECM WITH LOW COVERAGE CRISIS EVENTS[1)]

		Brand attention			*Brand strength*		
	Obs	*Expected sign*	*Estimated average coefficient*	*Z-Score*	*Expected sign*	*Estimated average coefficient*	*Z-Score*
Intercept	32	+/-	-.1324	-2.30 ***	+/-	.0505	5.07 ***
Advertising expenditures							
Immediate	32	+	.0086	3.61 **	+	-.0015	-2.01 **
Cumulative	32	+	.0379	5.00 ***	+	.0005	.07
Industry brand strength							
Immediate	32		-	-	+	.0353	8.47 ***
Cumulative	32		-	-	+	.0219	14.49 ***
Industry brand attention							
Immediate	32	+	.0688	20.47 ***		-	-
Cumulative	32	+	.0389	16.85 ***		-	-
Crisis event[2)]							
Immediate	78	+	-.0086	-.25	-	.0017	.21
Cumulative	78	+	-.0121	-.21	-	.0075	.20
Adjustment	32	-1< g <0	-.5560	-23.22 ***	-1< g <0	-.3884	-29.38 ***
Long-term Trend	32	no	-.1319	-11.77 ***	no	.0022	.95 ***

Notes: ** p < .05, *** p < .01 (two-sided).

[1)] We only included crisis events with media coverage < 3.

[2)] We identified a total of 103 crisis events with media coverage <3. We had to exclude 17 events because of missing information on control variables and 8 events due to confounding events.

Table G8.1
2SLS ESTIMATION RESULTS FOR ECM WITH ALL CRISIS EVENTS (NO CUTOFF)

		Brand attention			Brand strength		
	Obs	*Expected sign*	*Estimated average coefficient*	*Z-Score*	*Expected sign*	*Estimated average coefficient*	*Z-Score*
Intercept	69	+/-	-.1129	-3.63 ***	+/-	.0194	3.33 ***
Advertising expenditures							
Immediate	69	+	.0081	6.25 **	+	.0002	.20
Cumulative	69	+	.0265	8.77 ***	+	.0016	1.41 *
Industry brand strength							
Immediate	69		-	-	+	.0349	13.81 ***
Cumulative	69		-	-	+	.0241	23.51 ***
Industry brand attention							
Immediate	69	+	.0620	28.14 ***		-	-
Cumulative	69	+	.0340	22.50 ***		-	-
Crisis event							
Immediate	214	+	.0255	10.91 ***	-	-.0106	-14.54 ***
Cumulative	214	+	.0531	9.01 ***	-	-.0280	-10.30 ***
Adjustment	69	-1< g <0	-.5566	-33.89 ***	-1< g <0	-.3943	-43.99 ***
Long-term Trend	69	no	-.1114	-14.34 ***	no	.0030	.28 ***

Note: * p<.1,** p < .05, *** p < .01 (two-sided).

Table G8.2

WLS ESTIMATION RESULTS FOR DRIVERS OF BRAND EFFECTS FOR ECM WITH ALL CRISIS EVENTS

			Brand attention					***Brand strength***			
	Dependent variable:		***Estimated immediate effect***		***Estimated cumulative effect***			***Estimated immediate effect***		***Estimated cumulative effect***	
		Expected sign	*Coefficient*		*Coefficient*		*Expected sign*	*Coefficient*		*Coefficient*	
Intercept		+/-	-.076	(.105)	-1.051**	(.447)	+/-	-.053	(.043)	-.337	(.235)
Crisis type	*Product-harm crisis (base)*										
	CSI (average)	+/-	.040*	(.029)	-.075	(.160)	-	-.017**	(.010)	-.208**	(.101)
	Violation of fair operating practice	+/-	-.004	(.032)	-.287**	(.117)	+/-	.020	(.012)	.006	(.064)
	Human rights / working violation	+/-	.139***	(.028)	.170	(.107)	+/-	-.022**	(.011)	-.021	(.056)
	Environmental scandal	+/-	-.016	(.065)	-.109	(.293)	+/-	-.049**	(.020)	-.609***	(.125)
	Product-harm and CSI crisis	+/-	-.059**	(.030)	-.163	(.130)	+/-	.021	(.014)	.190**	(.079)
Crisis characteristics											
Media coverage		+	.025***	(.002)	.076***	(.010)	-	-.011***	(.001)	-.048***	(.006)
Crisis origin	*International (base)*		-		-			-		-	
	National	+/-	.068***	(.026)	.066	(.093)	-	-.027***	(.010)	-.105**	(.050)
Immediate firm reaction	*No reaction (base)*		-	-	-	-		-	-	-	-
	Deny responsibility	+/-	.012	(.029)	.068	(.099)	+/-	-.007	(.012)	-.056	(.058)
	Accept responsibility	+/-	.033*	(.019)	-.204**	(.096)	+/-	.035***	(.009)	.091*	(.052)
Brand & firm characteristics											
Product type	*Retail (base)*	-	-	-	-	-		-	-	-	-
	Non-Durables	+/-	-.012	(.055)	-.008	(.191)	+/-	.064**	(.026)	.239*	(.123)
	Durables	+/-	.046	(.028)	.277***	(.101)	+/-	.026***	(.010)	.031	(.055)
	Services	+/-	.038	(.033)	-.126	(.122)	+/-	-.029**	(.012)	.074	(.070)
Prior brand strength		-	-.001**	(.001)	-.004**	(.002)	+	$-9.5\text{x}10^{-4}$***	($2.3\text{x}10^{-4}$)	.002*	(.001)
Firm size		-	-.008	(.009)	.075**	(.037)	+/-	.009***	(.003)	.039**	(.018)
Crisis history		+/-	.000	(.003)	.005	(.013)	-	-.001	(.001)	-.011*	(.007)
$\mathbf{R^2}$			*.574*		*.261*			*.555*		*.324*	
N			*299*		*299*			*299*		*299*	

Notes: * p<.1, ** p<.05, *** p<.01. Tests are one-sided if clear directional effects are expected, two-sided if not. Standard errors in parentheses.

[1)] The coefficient for CSI (average) is the mean of the estimated coefficients for the three CSI-crisis types. The standard error is calculated from the associated variance-covariance matrix. We also estimated a model that includes a dummy variable for CSI event only (instead of three different types). Results are fully consistent with this table.

References Appendix Paper I

Bagozzi, Richard P. and Youjae Yi (1988), “On the evaluation of structural equation models”, *Journal of the Academy of Marketing Science*, 16 (1), 74-94.

Bharadwaj, Sundar G., Kapil R. Tuli, and Andre Bonfrer (2011), “The Impact of Brand Quality on Shareholder Wealth”, *Journal of Marketing*, 75 (5), 88-104.

Bentler, Peter M., and Li-tze Hu (1999), “Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternative“, *Structural Equation Modeling: A Multidisciplinary Journal*, 6 (1), 1-55.

Fornell, Claes and David F. Larcker (1981), “Evaluating Structural Equation Models with Unobservable Variables and Measurement Error,” *Journal of Marketing Research*, 18 (1), 39–50.

Rego, Lopo L., Matthew T. Billett, and Neil A. Morgan (2009), “Consumer-Based Brand Equity and Firm Risk,” *Journal of Marketing*, 73 (6), 47–60.

PAPER II: DO LAYOFFS HURT A FIRM'S BRAND ? – AN EVENT STUDY WITH CONSUMER MINDSET METRICS

Author: Max Backhaus

Abstract

Layoffs are usually undertaken to increase operational efficiency and financial performance but they often also entail negative effects on different stakeholders such as employees. Nevertheless, evidence on the dark side of downsizing with respect to decreasing consumer perceptions and ultimately decreasing sales and firm performance is scarce. To quantify the effects of layoff announcements on consumers this study extends the common event study methodology to non-financial performance measures based on a multi-national sample of 179 layoff announcements and 5 years of daily consumer mindset data across multiple sectors and firms. Results suggest substantial positive effects of layoff announcements on consumer brand attention and negative effects on brand strength. Moreover, the study identifies drivers that amplify or attenuate the effect on brand perceptions such as the number of job cuts, the strategic firm motive, and prior levels in brand perception. Hence, the findings provide an additional explanation why layoff decisions often do not achieve their strategic dictum to increase efficiency and reveal important drivers that moderate the effect of layoff decisions on consumer brand perceptions.

Keywords: Layoffs, consumer brand perception, mindset metrics, event study

1 Introduction

Downsizing decisions often result in cutting thousands of employees' jobs and are a regular means for companies to reduce costs (Chalos and Chen 2002). Layoff announcements are published almost every day in leading international, national, business, and public media and have become particularly prevalent since the financial crisis. The U.S. Bureau of Labor Statistics (2016) recorded on average 1508 annual mass layoff events in the U.S. between 2003 and 2013. The layoff announcements of Walmart and Schlumberger in the first quarter of 2016 comprising job cuts of 17,000 and 12,500 employees, respectively, are only two of many recent examples (Long 2016).

The underlying economic logic for these layoffs is quite simple: by reducing a part of the cost factor "labor", an increase in the company's competitiveness and profitability is triggered (Chen et al. 2001). This in turn leads to an increase in shareholder value and consequently a rising stock price. But this effect can only be observed if cost effects are independent of revenues.

Various studies examine whether corporate layoffs are indeed positively correlated to firm performance. The results suggest that short-term gains from cost reductions are possibly set off by long-term losses due to negative effects from layoffs on *organizational* performance. A reduction in workforce can lead to lower employee motivation (e.g. Brockner et al. 1994), decreasing skill bases (e.g. Amabile and Conti 1999), as well as lower service levels and product quality (Mishra and Mishra 1994). In fact, these outcomes of decreasing operational performance also negatively influence customer satisfaction (Williams, Khan, and Naumann 2011; Homburg, Klarmann, and Staritz 2012; Habel and Klarmann 2015). Customer satisfaction decreases are mainly driven by customers' expectations and personal experiences regarding product and service quality and lead to a deferred decline in financial performance (Habel and Klarmann 2015). Thus, it is not clear whether, or to what extent, layoffs really enhance efficiency and firm performance (Datta el al. 2010).

One aspect that has been largely ignored by literature is the negative effect layoff announcements might entail with regard to their *social* performance. Firm's social performance provides information about the behavior and characteristics consumers associate with and link to brands and firms (Aaker 1997). The announcement of layoffs signals information about the company's value system. Layoffs can be perceived as a breach of the psychological contract with stakeholders such as employees or customers (De Meuse et al. 2004). Therefore, they might violate increasing consumer expectations regarding firms' strategic behavior with respect to corporate social responsibility (Backhaus and Fischer 2016). Consumers corporate social responsibility associations are reflected in consumer brand perceptions (Brown and Dacin 1997). If layoff announcements are perceived as negative information about firm behavior they should also negatively affect consumers' identification with their brands and lead to changes in brand perceptions (Bhattacharya and Sen 2003). The value relevance of consumer mindset metrics has been proven repeatedly (Hanssens et al. 2014; Stahl et al. 2012) Thus, a negative effect of layoff announcements on consumer brand perceptions might additionally offset positive operational performance effects.

The few existing studies related to consumer's mindsets explore the consequences of layoffs on corporate reputation (Zyglidopoulus, 2005; Flanagan and O'Shaughnessy 2005; Love and Kratz 2009). Overall, results support a negative effect of layoffs on corporate reputation but the effect seems to diminish after 1992 (Love and Kratz 2009). Although these findings offer valuable insights into the effect of layoffs on firm reputation, no evidence exists that the results hold true for times of increasing transparency, digital consumer interconnectivity, and rising consumer expectations with regard to corporate social responsibility. Furthermore, prior literature builds its empirical analysis on annual data and does not account for an event-specific perspective. The studies also do not give much guidance concerning the drivers of the magnitude of layoff announcement effects on consumers. Hence, the transferability of findings to today's business environment has to be questioned.

This study tries to give answers to these questions and thus enhances the understanding of layoff decisions by analyzing the effects of real layoff announcements on consumers' mindsets. Table 1 positions the study at hand in comparison to related prior research.[7] Specifically, I investigate daily changes in consumer brand attention, brand strength, and brand rating dispersion immediately before and after layoff announcements are published. Brand attention and brand strength relate to the constructs of brand awareness and brand image as the key components of consumer-based brand equity (Keller 1993). In addition, recent studies have demonstrated the value relevance of heterogeneity-based mindset metrics (e.g. Luo, Raithel, and Wiles 2012). Hence, I also investigate the effect on brand rating dispersion as a volatility-based measure of brand perception.

Based on a multi-national sample of 179 layoff announcements in the U.S. and Germany during the time period 2008-2012 across 7 industry sectors and more than 108 firms, I extend the event study methodology to consumer mindset variables as the dependent variables of interest. Therefore, I provide a new disaggregate perspective on the daily level. This approach allows for the valid identification of effects. In the empirical analysis I also control for industry-wide effects, which are usually neglected in previous studies. Layoff decisions are regularly triggered by stagnating market demand or industry-wide economic effects. Hence, negative consequences from downsizing initiatives might not necessarily lead to

[7] The autor acknlowedges that other studies exist that study layoff effects in survey/interview settings using hypothetical events. However, a drawback of such research is that insights are obtained under a hypothetical layoff setting. This limits the transfer of results to real, dynamic markets.

weaker competitive positions since the majority of firms might need to cut costs and jobs (e.g. the banking industry during the financial crisis). Furthermore, in order to identify moderators that intensify or attenuate announcement effects on consumers, in a second step, I also perform cross-sectional moderator analysis.

In summary, the study offers three distinct contributions to the existing findings. First, it offers a new perspective and insights into the effects of layoff announcements on consumer brand perceptions. The results are valuable to managers because they help understand which layoff events have the potential to significantly hurt consumer brand perception. In such cases firms should use media and marketing communications to counter brand perception drops. Second, the study provides an additional theoretical and empirical explanation of negative stock market reactions to layoff announcements, which supports the hypothesis that "hidden costs" may outweigh operational efficiency gains from downsizing measures. Moreover, the results can inform investors to better evaluate the financial impact of layoff decisions and enables them to refine their firm valuations accordingly. Third, I extend the existing event study methodology to generate new insights from high frequency consumer data. The study sets the grounds to transfer and apply event studies in various non-financial-related settings accounting for the new data landscape in marketing and market research. In particular, I discuss the critical steps of modeling expectations in order to estimate abnormal changes in the dependent variable as well as the proper identification of confounding events. Market research companies have recently begun to collect, track, and process such disaggregate, comprehensive consumer data (Katsikeas et al. 2016). These data are available to the majority of B2C firms in many countries all around the globe. Thus, managers and researchers can use the theoretical underpinning of the extended event study methodology to study the effects of different events with similar data as it is shown to serve as useful alternative indicators for changes in brand and financial performance of firms.

The results show that layoff announcements cause significant positive abnormal returns in the brand attention measure and significant negative abnormal returns with respect to brand strength. However, the effect on brand attention diminishes after about a week, whereas the negative effect on brand strength does not. No significant effects can be detected with respect to brand rating dispersion. That is, the overall effect of layoff announcements is especially driven by the negative effect in brand strength. Concerning the drivers of the effect on brand strength the size of the layoff and high prior brand attention amplify the negative effect of layoff announcements, whereas prior brand strength attenuates the effect. Reactive layoffs gain more brand attention by consumers than proactive ones and prior brand attention also increases the effect on current brand attention.

Table 1: Empirical Research on the Effects of Layoffs on Consumer Mindset Metrics

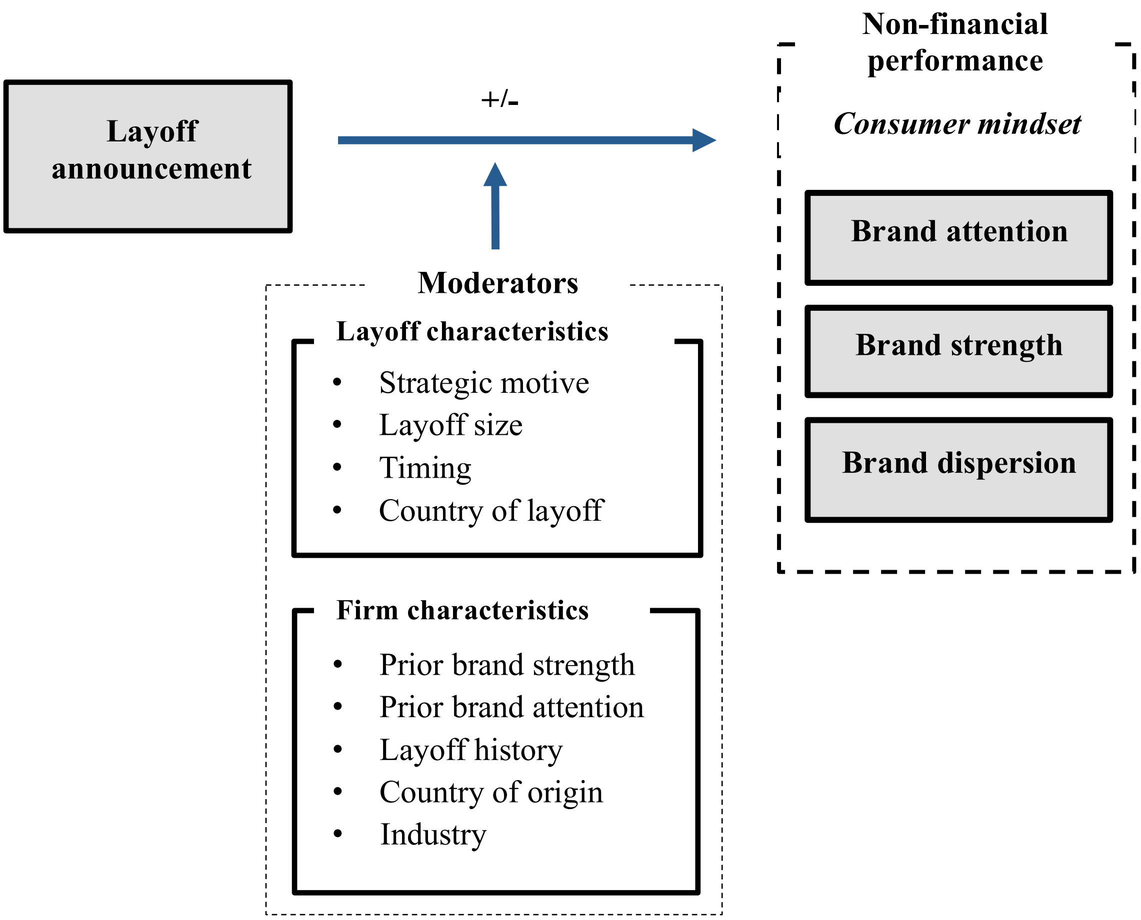
Reference	Mindset metric	Model	Dependent variable(s)	Time period	Aggregation level	Layoff data	Moderator analysis	Event logic
Williams, Khan, & Naumann (2011)	Customer satisfaction	Static-group comparison (t-test)	Customer satisfaction (single-item scale) before and after layoff	2002	Quarterly	One-time layoff event (N=1)	No	Yes
Homburg, Klarmann, & Staritz (2012)	Customer satisfaction	Linear regression	Perceived customer satisfaction (one-item scale)	n.a.	5 year time horizon	Database search (N=109)	No	No
Habel & Klarmann (2015)	Customer satisfaction	Linear regression	American Customer Satisfaction Index (ACSI)	1994-2007	Annual	Reduction in employees Compustat database (N=153)*	No	No
Zyglidopolous (2005)	Corporate reputation	Linear regression	Fortune's AMAC survey	1889, 1991	Annual	Reduction in employees in AMAC database (N=145)	No	No
Flanagan & O'Shaugnessy (2005)	Corporate reputation	Linear regression	Fortune's AMAC survey	1996-1998	Annual	Media coverage of layoff decisions (N=72)	No	No
Love & Kratz (2009)	Corporate reputation	Rank-ordered logistic regression	Fortune's AMAC survey	1984-1994	Annual	Media coverage of layoff decisions (N=91)	Yes	No
This study	Consumer brand perception	Event study	Brand strength, brand attention, brand dispersion	2008-2012	Daily	Media coverage of layoff decisions (N=179)	Yes	Yes

Notes: AMAC = America's Most Admired Companies, ACSI = American Customer Satisfaction Index
*The authors also include a robustness analysis with media layoff announcements.

2 Conceptual Framework

Figure 1 shows the conceptual framework of my study. I analyze the effects of layoff announcements on brand attention, brand strength, and brand rating dispersion. I define layoffs as a permanent reduction of a significant number of employees from the payroll of an organization (Freeman and Cameron 1993). If business and public media report about a planned or conducted downsizing initiative that includes laying off workforce, this incident is called layoff announcement.

Figure 1: Conceptual Framework of the Effect of Layoff Announcements on Consumer Brand Perception



2.1 **Focal Brand Performance Metrics**

Brand attention measures the level of awareness due to the amount of available positive or negative information about the brand. Brand strength is a composite measure that covers several image and performance dimensions of a brand as perceived by the consumer. Conceptually, both brand awareness and brand image are the constituent parts of Keller's (1993) model of customer-based brand equity. Beyond the average brand strength, brand dispersion offers a new dimension and deeper understanding of a brand's health reflecting the spread between brand haters and brand lovers. Dispersion is the "heterogeneity in brand quality ratings, which may reflect inconsistency and polarization into brand lovers and haters" (Luo, Raithel, and Wiles 2013, p.400). Higher heterogeneity in consumers' brand evaluations poses a threat to firms because it reduces a firm's brand equity (Luo, Raithel, Wiles 2013). High dispersion thus reveals a stretched, inconsistent brand image among consumers. I provide more measurement details on these metrics in the data section and Appendix A.

2.2 **Hypotheses Development**

Brand equity theory posits that consumers accumulate experiences and information over time which build the basis for brand awareness and brand image (Keller 2008). Layoff announcements serve as negative signals to consumers with respect to product and service quality (Habel and Klarmann 2015) and trigger decreases in expectations regarding consumer orientation (Subramony and Holtom 2012). Moreover, downsizing initiatives resulting in mass layoffs can be perceived as a breach of the psychological contract between the firm and its employees (De Meuse et al. 2004). Significant layoff announcements are usually covered broadly also in public media. News coverage about firm behavior, whether positive or negative, is publicity that can increase brand attention (Berger, Sorensen, and Rasmussen

2010). Layoff announcements serves as (new) information about a firm's behavior and should impact consumers' attention towards a firm's brand. Consequently I formulate

H1*: Layoff announcements increase brand attention.*

Brands serve different functions for consumers (Fischer, Völckner, and Sattler 2010). In addition to reducing the risk related to functional benefits (risk reduction function), brands can also provide symbolic benefits allowing consumers to project their self image (Levy 1959). The social demonstrance function of brands can be affected if consumers learn about layoff decisions. Given the limited information available that consumers can draw on to build their overall perceptions of a firm, layoffs can be perceived as a negative signal concerning a firm's character, credibility, and ethical responsibility (Love and Kratz 2009). If consumers evaluate layoffs as unethical and as an act of corporate social irresponsible behavior (Zyglidopoulos 2005), layoff announcements can be classified as negative news about firm behavior. Thus, they may severely harm the trust and confidence consumers place in brands and lead to decreases in brand strength (Ahluwalia, Burnkrant, and Unnava 2000):

H2*: Layoff announcements have a negative effect on brand strength.*

Finally, consumers interpret new information differently and therefore any new information that is relevant to the consumers' brand perception leads to polarization of opinions among consumers (Lord et al 1979). Based on confirmatory bias theory consumers evaluate information and move further apart in their evaluations when initial beliefs differ. The underlying reason is that individuals tend to process new information with different personal and situational processing goals, such as to defend their prior beliefs or to manage their impression with others (Ahluwalia 2002). Consequently, a layoff announcement bearing new information will increase heterogeneity in consumer brand ratings leading to higher brand rating dispersion. It follows that

***H3**: Layoff announcements have a positive effect on brand rating dispersion.*

2.3 Moderators of Brand Performance Effects

The relation between layoff announcements and brand performance measures might be moderated by layoff characteristics since every layoff event is different. I account for moderators that have been shown to influence the effects of layoff announcements on other mindset metrics such as customer satisfaction or corporate reputation. Specifically, I consider the strategic motive of the layoff decision (proactive vs. reactive decision), the timing of the layoff (whether the layoff announcement was made during the financial crisis between 2008 and 2009 or afterwards), the layoff size (the number of employees laid off), and the country where the layoff was announced (country of layoff announcement).

Strategic motive. While some companies reduce their workforce proactively to enhance organizational performance, others downsize reactively as a necessary decision to financial distress (Chen et al. 2001). I expect that consumers react differently to these different motivations. Prior research shows that laying off workforce may act as a strong signal regarding a firm's "character" (Love and Kraatz 2009). Consumers perceive layoffs as particularly opportunistic if the company enjoys profits. In contrast, consumers may perceive companies that reduce their workforce to counter losses as less unfair and less socially irresponsible. Indeed, the negative effect of downsizing on corporate satisfaction is smaller if downsizing is a reaction to performance problems of a firm (Habel and Klarmann 2015). In summary, I expect stronger negative effects on brand strength in a proactive layoff setting. I do not formulate specific expectations since effects are less clear with respect to brand attention and brand rating dispersion.

Timing of layoff. As more firms layoff workforce across the population, the social costs of downsizing for any single firm decreases. If a single firm reduces workforce, its deviant behavior is likely to draw much attention and social censure (Flannagan & O'Shaugnessy

2005). Hence, in times of many overall layoffs such as during the financial crisis from 2008 to 2009, I expect an attenuated brand attention, brand strength, and brand dispersion effect.

Layoff size. The number of employees laid off in downsizing situations is crucial. The greater the magnitude of a layoff the more information it should convey to consumers. Larger layoffs will also be discussed more in the media, as well as in-between consumers offline and online. Consequently, I except stronger effects for all three performance measures.

Country of layoff announcement. Consumer responses to layoff announcements might also differ due to cultural differences. Consumer research suggests that country populations differ in their value systems (Hofstede 2003). In individualistic cultures personal accomplishments, ideas, and goals are emphasized. On the other hand, in collectivist cultures the emphasis is on group norms and values and the overall welfare of the society is more important than the individual's welfare. Hence, in collectivistic, as compared to individualistic cultures, firm relationships with employees are stronger and valued as more important by consumers (Lewin, Biemans, and Ulaga 2010). In my empirical analysis I compare reactions of German and U.S. consumers. The U.S. is known as rather individualistic society compared to Germany (Fischer, Völckner, and Sattler 2010). Hence, German consumers might stronger dislike and blame firms for downsizing initiatives and in turn stronger negative brand strength effects. Consequently, I also expect more attention by media and consumers for firms that downsize workforce, which leads to higher brand attention and greater brand rating dispersion.

In addition to the layoff event itself, firm-specific moderators such as prior brand awareness, prior brand strength, prior downsizing history, industry affiliation, and country of origin can aggravate or attenuate the effect of layoffs announcements on consumers.

Prior brand attention. High brand attention indicates high awareness. If consumers hear about brands that they know and usually talk or hear about, they might take notice of the layoff information to adjust brand perceptions. It therefore seems reasonable to expect that firms that exhibited higher prior brand attention will be punished and discussed more by consumers. On the other hand, high prior brand awareness might lead to smaller attention gains since the overall level is already high (marginal returns). Hence, following Berger, Sorensen, and Rasmussen (2010), with respect to brand attention I expect a reverse effect. With respect to brand rating dispersion I do not formulate a clear directional expectation.

Prior brand strength. A firm's prior brand strength should affect consumers' interpretations of its actions (Backhaus and Fischer 2016). To the extent that brand strength is a sticky and enduring asset cumulated through a history of making actions, I expect prior brand strength to serve as a protection against the negative effect of a layoff event on brand strength. Similarly, I also expect prior brand strength to serve as a buffer against rising brand rating dispersion. Concerning brand attention, Berger, Sorensen, and Rasmussen (2010) argue that the gain in awareness due to negative publicity is lower the stronger a brand is. Following their line of argumentation, I expect a negative moderation effect of prior brand strength with respect to the effect on brand attention.

Prior layoff history. Layoff history indicates whether the event is a one-time event or part of a pattern of similar crises. A history of layoff announcements suggests an organization has an ongoing problem that needs to be addressed. The observer learns that the firm has a tendency to act in this way over time, which increases the evidence for causal culpability (Zautra et al. 2005). People should be inclined to give the benefit of the doubt to firms with a record of "good behavior" and to be less quick to attribute opportunism on the basis of a single strategic decision. Therefore, I expect a negative effect on brand strength and a positive effect on dispersion from the amount of prior layoffs. The effect on the brand attention, however, is not clear.

Industry. Some industries have a worse reputation than others among the population in general. For example, banks are often depicted as "evil" in the media since the financial crisis in 2008/2009. Hence, negative incidents in such industries gain more attention and are weighted stronger by consumers than in other industries. On the other hand, consumers might have already very low expectation with respect to corporate social performance of financial institutions. This would indicate that negative results will be smaller because consumers have already considered them to behave badly and layoff information do not really depict new information. Since it is difficult to draw well-founded inferences about the role of industry characteristics I do not formulate a priori expectations.

Country of origin. Empirical research shows that more articles are written about a firm announcing layoffs when the owners are foreigners, and, on average, more of the words written concern downsizing rather than other topics, such as firm performance, and products (Friebel and Heinz 2014). Additionally, consumers might attribute more blame to foreign firms' downsizing decisions than domestic ones. I thus expect stronger brand attention and brand strength effects for foreign firms. The expectations regarding brand rating dispersion are less clear and thus I do not formulate explicit expectations.

3 Data and Descriptives

3.1 Data Collection

My objective is to apply the event study methodology to estimate and explain the effect of layoff announcements on brands (see Figure 1 again). In order to do so I analyze layoff announcements in combination with brand time-series data. Specifically, I draw on five years of daily data from the U.S. and Germany in the period 2008 to 2012, which constitutes the sample of this study.

Consumer mindset metrics. The consumer mindset data is based on a unique database that offers a nationwide measurement of brand perception at the daily level across various countries. The YouGov group, a global market research company specializing in online panels, collects this data. Their online panel consists of over 4 million panelists across 37 countries including 2 million panelists in the U.S. and Germany. I obtained data from 2008 to 2012 for a total of over 2000 brands across twenty different industry sectors in U.S. and German market.

Table 2: Descriptive Statistics of Layoff Announcements

		N	%
Total events identified		272	-
Company brands		148	-
Layoff events per brand		1.84	-
Confounding events		56	21%
Overlap or missing data in estimation window		37	14%
Final sample		179	-
Company brands		108	-
Layoff events per brand		1.66	-
Country			
United States		50	28%
Germany		129	72%
Year			
2008		26	15%
2009		43	24%
2010		18	10%
2011		31	17%
2012		61	34%
	Company brand examples		
Industry			
Consumer staples[1]	Pepsi, L'Orèal	14	14%
Consumer appliances	Panasonic, Whirlpool	33	33%
Other consumer discretionary[2]	Nike, Karstadt	19	19%
Digital life & media	EA Games, Yahoo!	19	19%
Automotive	GM, Shell	26	26%
Financial services	Goldman Sachs, UBS	33	33%
Non-financial services	AirFrance, TNT	35	35%

Notes:
[1] Includes food & gastronomy, household & personal care, and OTC & healthcare categories
[2] Includes apparel & fashion as well as retailing

Brand attention represents the number of respondents who are aware of either negative or positive news about a brand. Brand strength is measured along six dimensions, which are aggregated to the YouGov BrandIndex. These dimensions are perceptions of: brand quality, brand value, brand satisfaction, brand recommendation, brand identification, and brand overall impression.[8] Assuming that the negative, neutral, and positive answer options represent a 3-point likert scale, brand rating dispersion is calculated as the standard deviation of the brand strength measure. Table 3 offers general information on variable definitions, measurement, and operationalization. Details on the exact items and the collection of data are provided in Appendix A.

The big advantage of the BrandIndex over other brand strength measures such as Young&Rubicam's BAV (e.g., Stahl et al. 2012) is that it is available at the disaggregate, daily level. This allows for detecting changes in brand perception triggered by single events such as press reports on layoff announcements in a precise and unique manner.

At the aggregate brand level, brand attention scores fall within the range of 0 to +100 and brand strength scores fall within the range of -100 to +100. For brand strength, as an example, the extremes are only realized if all respondents agree in their negative or positive perception of the brand relative to its competitors. In order to estimate returns for brand strength I rescale the variable to run from 0 to 200. Brand dispersion scores are variance measures by definition in this are not range-restricted with respect to a maximum. The daily brand ratings are based on a large sample of 100 respondents on average.

Layoff announcements. I collected data on layoff announcements through an extensive media search with regard to the specific events in leading media sources in the U.S. and Germany using the Lexis Nexis and ProQuest databases (details on the data collection procedure are provided in Appendix B). I generated a pre-tested list of keywords (like

[8] In 2013, YouGov expanded the number of items in the survey, among them questions on purchase consideration and intent. The observation period in this study ends before this change.

"downsizing", "layoff", "job loss", "cost cutting" etc.) and systematically searched for the keywords in connection with the specific brand (see again Appendix B for details).

Overall the search identified 272 layoff announcements events within the time frame from 2008 to 2012 (see Table 3) that match the brands in the YouGov database.[9] 37 cases had to be excluded because there was missing an overlap of events with regard to estimation and event window or missing data on control variables (e.g. missing information on layoff size). I had to exclude another 56 cases due to confounding events such as new product introductions, etc. (see details in the methodology section). Thus, my final sample size covers 179 layoff announcements (see Appendix B for the list of events) across 10 industries, 108 brands, and 5 years of daily data. I define the day, in which the first media report was published on the event, as the event date.

Moderator variables. I obtain data for the moderator variables based on the press research of layoff announcements and from the YouGov database. For layoff-specific moderators three coders read every report related to a specific layoff announcement. The number of workers to be laid off (layoff size) is usually provided in the article (> 90% of all announcements). Announcements that did not reveal the actual size of the layoff have been excluded. The articles also inform about the date when the announcement was made and whether it is published in German or U.S. media (country of layoff). Based on the content information of the articles the coders also determined whether the layoff can be classified as a proactive action, aiming at increases in efficiency, or a reactive action due to bad prior financial performance and/or reduced demand (Love and Kraatz 2009). Coding agreement is greater than 97% for all coded moderator variables. Remaining disagreements were solved by discussion.

[9] Since I did not have access to YouGov data from the U.S. before January 2009, layoff announcements in the U.S. in 2008 are not included in the empirical analysis.

Prior brand attention and prior brand strength are the focal brand's averages for both measures in the estimation window (60 days) before the respective event. Layoff history measures the number of remembered announcements for the focal brand. I apply a time weight to the accumulation to account for the process of forgetting. This weighting also alleviates potential censoring issues that are associated with this variable.

Country of origin is defined as the location of the headquarters as well as the main listing of the firm. Industry classification is determined as a combination of the global industry classification standard (GICS) as well as the YouGov industry classification. Table 3 informs about the details of measurement for each variable.

3.2 **Descriptives Statistics**

Table 3 provides descriptive information about the sample. Brand attention, brand strength, and brand rating dispersions show strong variation. SD is larger than the mean for brand strength and relatively high for brand attention and brand rating dispersion compared to the mean values. The lower part of Table 3 shows the descriptive statistics for the moderator variables. The average layoff size is 4,009 and the majority of the announcements are published in German media (71%). 39% of all layoff announcements took place during the financial crisis (2008-2009) and 34% were reactive layoffs decisions. 110 layoff announcements (62%) concerned domestic companies. Companies for which at least one layoff announcements was detected, initiated 1.84 downsizing initiatives within the time period of 2008-2012. This results in an average of .78 for layoff history. To summarize, the variation in the data is strong supporting the proper identification of effects.

Table 3: Variable Definitions and Summary Statistics

Variable	**Measure / Operationalization**	**Data sources**	**N**	**M**	**SD**
Layoff announcement	First day a leading newspaper informed about the layoff announcement. Dummy variable indicating the announcement of layoff (=1 on event day; 0 = no event day)	Press research (LexisNexis, ProQuest)	179	-	-
Brand performance measures					
Brand attention [0;100]	Index from 0 to +100 aggregated across 6 brand perception dimensions: brand quality, brand value, brand satisfaction, brand recommendation, brand identification, brand overall impression. $Attention\ score_{i,t} = (positive_{i,t} + negative_{i,t}) / (positive_{i,t} + negative_{i,t} + neutral_{i,t}) * 100$	YouGov	614,008	17.36	12.02
Brand strength [0;200]	Index relating to the question whether respondents have heard anything positive or negative about the brand within the last 2 weeks. $Strength\ score_{i,t} = [(positive_{i,t} - negative_{i,t}) / (positive_{i,t} + negative_{i,t} + neutral_{i,t}) * 100] + 100$	YouGov	618,048	114.1	17.90
Brand rating dispersion [0;∞]	Standard deviation of daily customer brand strength score $Disp_{t,i} = \sqrt{(1-\mu_{t,i})^2 * \%negative_{t,i} + (2-\mu_{t,i})^2 * \%neutral_{t,i} + (3-\mu_{t,i})^2 * \%positive_{t,i}}$ $with\ \mu_{t,i} = 1 * \%negative_{t,i} + 2 * \%neutral_{t,i} + 3 * \%positive_{t,i}$	YouGov	618,048	.48	.11
Layoff-specific moderators					
Strategic motive[a]	Reactive layoff: the firm justifies the layoff by economic downturns or as a reaction to demand shifts. Proactive layoff: the firm refers to general productivity and efficiency gains independently from its' financial status or general economic conditions. Dummy variable (=1, if layoff announcement is reactive) for firm i at event day t	Press research	179	.34	.48
Layoff size	Number of layoff size of firm i at event day t	Press research	179	4,009	6,310
Timing of layoff[a]	Dummy variable indicating whether the layoff announcement was made during the financial crisis (=1 if layoff between 2008 and 2009; =0 otherwise)	Press research	179	.39	.49
Country of layoff announcements[a]	Dummy variable indicating the country in focus (=1 if Germany, =0 if U.S.)	Press research	179	.71	.45
Firm/Brand-specific moderators					
Prior brand strength	Level of brand strength prior to the event (average brand rating in estimation window)	YouGov	179	12.10	17.77
Prior brand attention	Level of attention prior to the event (average brand attention in estimation window)	YouGov	179	18.54	10.03
Prior layoff history	Remembered (time-discounted) number of layoff announcements since 2008 until focal layoff event	Press research	179	.78	.98
Industry	Dummy variables for industry affiliation based on GICS-classification and YouGov industry classification.	Thomson DataStream	179	-	-
Country of origin[a]	Dummy variable indicating whether the headquarter and listing of firm is domestic or foreign(=1, if domestic; =0 if foreign)	Press research	179	.62	.49

[a] For these variables, we report the percentage of observations having the value of 1.

4 Event Study Methodology

4.1 Premises of Event Studies

The event study method is a widespread and frequently used technique to measure the effect of an economic event on a firm’s value. Although event studies root in the financial literature (Fama et al. 1969), a multitude of applications also exist in marketing research to study the effects of marketing-related events such as product innovations (Agrawal and Kamakura 1995), internet channel additions (Geyskens, Gielens, and Dekimpe 2002), customer satisfaction (Fornell et al. 2006), brand acquisitions and disposals (Wiles, Morgan, and Rego 2012), or product recalls (Gao et al. 2015) on stock performance.

Regardless of the specific research topic, event studies are based on the same principle: Since it is only possible to observe returns for the focal firm exposed to the event of interest, a counterfactual is needed to interpret the average price reaction to the event. Therefore, event studies differentiate between the stock market returns that would have been expected if the analyzed event would not have taken place (expected returns) and the returns that were caused by the respective event (actual returns; MacKinlay 1997). The difference between the actual and the expected returns (abnormal return) indicates whether there is a significant effect associated with the unexpected information revealed in the event. This way, a reliable conclusion about the price impact of specified events can be drawn (McWilliams and Siegel 1997).

The new availability of mindset data has drawn increasing attention by researches and practitioners (Katsikeas et al. 2016). These metrics measure the vast amount of non-transactional data that marketers can collect on individual and aggregate consumer level today. Key performance indicators such as brand performance, perceived quality, customer satisfaction, or attitudinal loyalty facilitate the economic analysis of consumer behavior (e.g. the drivers of customer lifetime value, Kumar and Reinartz 2016). In this context, it is not surprising that consumer mindset metrics have become part of a set of marketing key performance indicators that are tracked constantly by marketing research companies. Several firms evaluate and track brand performance (e.g., Interbrand, YouGov, Equitrend). This means that data availability for many firms for focal and counterfactuals on disaggregated time levels is very high, which is a necessary precondition for the successful application of event study analyses. As a result, consumer mindset metrics constitute a particular promising application as an integral part of customer-based brand equity and a central construct in marketing theory and practice.

4.2 **Empirical Strategy**

While there is no unique structure of an event study, there is a general flow of analysis (MacKinlay 1997, McWilliams and Siegel 1997). Figure 2 outlines the step-by-step approach of event studies and compares the classical application in a financial market context with the extended application to non-financial performance metrics, namely brand strength, brand attention, and brand rating dispersion. In the remainder of this chapter I will discuss each step in more detail and draw particular reference to the case of layoff announcements.

1. Definition of Event

In order to examine the reaction to an event, first the event has to be defined. An event can be any new information about a company that is valuable to investors or consumers (Brown and Warner 1985). The crucial characteristic is the novelty of the information embedded in the event (McWilliams and Siegel 1997). With respect to marketing-based performance measures layoff announcements might send negative signals to the consumer regarding the corporate social performance of a company but can also lead to an anticipation of decreasing service levels and technical efficacy (Love and Kraatz 2009). Usually, layoff announcements represent information that consumers cannot anticipate. This is because layoff plans do not leak to consumers before the announcement in leading media, which either are the very first to uncover layoff plans or pick up very quickly on information about closing of plants or restructuring plans (Friebel and Heinz 2014). Even if consumers anticipate a general trend of downsizing due to previous layoffs or the overall economic development, these expectations should not be embedded in brand perception measures before the announcement.

2. Event Date and Event Window

I define the event date as the day when media first reported about the layoff. Friebel and Heinz (2014) argue that in case of a layoff announcement all media outlets receive a standard notice circulated by central press agencies (e.g., DPA in Germany, AP or Bloomberg News in the U.S.). This assures that the majority of media coverage is central and immediately located around the day of the detected announcement.[10]

Second, the event window is set to the day preceding the announcement [-1; 0] and the days immediately following from 1 to a maximum of 10 weekdays [0; 10].[11] With respect to brand performance measures it seems reasonable that markets are not fully efficient. That is, not all consumers receive and process news immediately but with a time lag over the next few days. This is also due to the fact that not all media report about news on the exact same time; it is rather a dynamic process and usually media report on a specific event of interest more than once (Sandman and Paden 1979). Hence, I allow the event to have an effect over the two weeks following the first layoff publication. In the Appendix D I also provide results on the robustness with regard to a three day pre-event window. Results suggest that there is no leakage prior to the day before the first announcement.

[10] In cases where the layoff announcement was published on a Saturday or Sunday, the event date is set to the following Monday, since YouGov does not collect brand perception data on weekends.

[11] 10 days equals 2 weeks, since YouGov does not collect data on weekends (Saturdays and Sundays).

Figure 2: Comparison of Classical and Extended Event Study Approach

Empirical strategy	Classical event study (stock return / firm value metric)	Extended event study (marketing-based performance metric)
1. Definition of the event of interest	Selection of events bearing new information with potential impact on *firm value* (e.g., earnings announcements, M&As, macroeconomic announcements, new product introductions, recalls,...)	Selection of events bearing information with potential impact on *consumer mindsets* (e.g., new product introductions, recalls, channel extensions, testimonial signing,…)
2. Definition of event date and window	• *Event date:* when market can anticipate news regarding the defined event • *Event window:* market efficiency → short time frame before and after the event date	• *Event date*: first media publication • *Event window*: account for inefficiency in consumer response → time frame with sufficient periods for consumers to pick up and process information through media and word-of-mouth
3. Detection of confounding events and exclusion of affected focal events	Detection of further *firm-value* (see 1.) relevant information with regard to focal firm that is published within event window	Detection of all *consumer-relevant* (see 1.) information with regard to focal firm that is published within event window
4. Estimation of expected normal and abnormal returns	• Assumptions: – Market efficiency and rational expectation hypothesis – Event entails unanticipated information to investors • Definition of relevant market (Stock market index)	• Assumptions: – CBBE framework: prior information and expectations are embedded in mindset before event – Event entails unanticipated information to consumers • Definition of relevant market (Market analysis)
5. Significance testing of abnormal returns	Application of parametric and/or non-parametric tests accounting for specific assumptions.	
6. Cross-sectional moderator analysis	Develop and explain theory for cross-sectional variation in abnormal returns and test for the effects.	

Figure 3: Classification of Consumer-related Confounding Events

A) Product-/market-related events	Examples from empirical study
Product • New product introductions • Product recalls	• Launch of new Blackberry 10 system (Blackberry) • Presentation of new 5 series Touring (BMW)
Price • Price increases • Price discounts/promotions	• Permanent price increases in transportation fairs (Deutsche Bahn) • Massive price cuts before Christmas season (Otto)
Distribution • Changes in distribution networks	• New openings of shops in rural areas (IKEA)
Communication • Sponsorship announcements / events • Testimonial related news	• -
B) Behavioral/organizational-related events	
Corporate social (ir-)responsibility • Launch of CSR initiatives	• -
• CSI scandals – Violation of fair operating practices – Violation of human rights / working conditions – Environmental scandal	• Federal fines related to financial crisis (Deutsche Bank) • Corporate spying scandal (Deutsche Bahn)
Organizational changes • Layoff/Downsizing initiatives • Management changes	• CEO and management change (BP)
External shocks	• Fukushima earthquake (Panasonic)

3. Confounding Events

The event study methodology assumes that researchers are able to isolate the effect of an event from the effects of other events. Ignoring to control for confounding events will lead to a systematic estimation bias. Consequently, one of the most crucial elements when conducting an event study is the control for confounding events (McWilliams and Siegel 1997). In order to do so, it is necessary to conduct a thorough analysis to detect possible confounding events before, on, and after the event date (within the event window). For the detection of confounding events in event studies with marketing-based performance the event definition from financial research frameworks cannot be applied straight away (see 1.). Hence, a new typology of possible confounding events is needed. I provide a list of possible confounding events in Figure 3. To capture events that constitute a confounding character with respect to consumer perception, I differentiate between (a) product-/market-related events (e.g., new product introductions, product recalls, changes in price or distribution strategies) and (b) behavioral-/organizational-related events (announcements of corporate social irresponsibility initiatives, organizational changes, or external industry shocks). In total, my search for confounding events resulted in the detection of 56 confounding events during the estimation and event window, which lead to the deletion of the focal event from the sample.

4. Estimating Abnormal Returns

Event studies aim to determine if there is an abnormal change in the performance measure that can be attributed to the specific event. For this, the actual return has to be compared to an expected return. The expected return equals the hypothetical return that would have occurred in the absence of the focal event. The abnormal return for performance measure k (= brand strength, brand attention, and brand rating dispersion) on day t for brand i is calculated as the realized return R_{kit} minus the expected return $E[R_{\mathrm{kit}}]$

$$AR_{kit} = R_{kit} - E\left[R_{kit}\right] \tag{1}$$

$$\text{with} \quad R_{kit} = \frac{K_{i,t} - K_{i,t-1}}{K_{i,t-1}} \tag{2}$$

where K is the actual realization (observation) of the performance measure k (see Table 3 again for the definition of performance metrics). Correct specification of the counterfactual, expected return is critical for the successful application of the method (McWilliams and Siegel 1997). To estimate expected returns, I use three methods that are frequently used in current event study applications: mean-adjusted returns, market-adjusted returns, and market- and risk-adjusted returns (Brown and Warner 1985, Corrado 2011).

Constant mean returns. The mean return model does not rely on economic theory but solely on statistical assumptions (MacKinlay 1997). Thus, it is a pure statistical forecast model that builds its expected returns (forecasts) on historical realized returns in the estimation period and assumes a constant mean return

$$R_{k,i,t} = \mu_i + \varepsilon_{kit} \tag{3}$$

$$\text{with } \mathrm{E}\left[\varepsilon_{kit}\right] = 0 \text{ and } \mathrm{Var}\left[\varepsilon_{kit}\right] = \sigma_{\varepsilon,ki} \, .$$

The application is a rather simple comparison of the event date return with pre-event mean returns, which are estimated as

$$\mathrm{E}\left[R_{k,i,t}\right] = \mu_i \, . \tag{4}$$

Hence, the mean return model does not use any firm-specific information from market-wide information affecting the individual return. In cases where no economic theory is used, the best forecast model should minimize forecast errors in the absence of events. However, Brown and Warner (1985) show that the simple model fits quite well to stock market data and often provides similar results to more sophisticated models.

If alternative performance measures such as consumer mindset metrics exhibit return characteristics that are in line with the basic assumptions of event studies (that is, the errors are normally independently distributed) the application to marketing-based performance measures is straightforward. This is because there is no underlying economic theory to consider (MacKinlay 1997). In this study, I include the results of the mean return forecasts for comparison.

Market-adjusted returns. The more common approach in current event studies is to compare returns in the focal variable to average market returns (Wiles, Morgan, and Rego 2012). Hence, these average returns establish a control group of a set of firms that are not confronted with the event under investigation. Therefore, this event study design, although not completely rigorous and fully randomized, resembles a controlled, repeated quasi-experiment (Backhaus and Fischer 2016).

A first approach that includes information from the control group is to use market-adjusted returns. Here, the expected return for individual i is simply set to the overall market return

$$R_{k,i,t} = R_{m,t} + \varepsilon_{kit} \tag{5}$$

with

$$\mathrm{E}\left[R_{k,i,t}\right] = R_{m,i}\ . \tag{6}$$

As a result, abnormal returns depict the difference of realized returns for individual i to the market return. The application of such a research design is more than common in marketing and consumer research (Chen, Ganesan, and Liu 2009). My data set comprises brand performance information on the focal brand variables as well as for a group of a minimum of 10 and up to 25 competitive brands (see Table 2 for information on industries). This set establishes the control group and is used for the calculation of the expected market return of brand strength, brand attention, and brand rating dispersion.

Market model returns. Market models assume that a stable (linear) relation between market-wide factors such as the market return and the individual return exists (MacKinlay 1997). However, in comparison to the market-adjusted return models they allow for the inclusion of specific market factors (beyond the mean market return) and for variation in the individual performance metrics (Brown and Warner 1985).

Many market models only account for one market-related factor which is the mean market return. Such one-factor models are applied in the vast majority of marketing-related event studies (e.g., Agrawal and Kamakura 1995; Geyskens, Gielens, and Dekimpe 2002; Swaminathan and Moorman 2009; Homburg, Vollmayr, and Hahn 2014). In this study I also apply the one-factor model.[12] The return of brand strength, brand attention, and brand rating dispersion is defined as

$$R_{k,i,t} = \alpha_i + \beta_i R_{m,it} + v_{kit} \tag{7}$$

$$\text{with } \mathrm{E}\left[v_{kit}\right] = 0 \text{ and } \mathrm{Var}\left[v_{kit}\right] = \sigma_{v,ki} ,$$

where R_m denotes the return on day t for the performance measure of the overall market and the parameters α, β specify the linear structure of the market model. The expected return is than calculated based on the estimated regression parameter $\hat{\alpha}$, $\hat{\beta}$ from the estimation window:

$$E\left[R_{k,i,t}\right] = \hat{\alpha}_i + \hat{\beta}_i R_{m,it} \ . \tag{8}$$

The economic theory for the application of market models to consumer mindset performance measures roots in consumer research. First, structural heterogeneity in consumer mindset metrics evolution across brands should be accounted for since brand-specific attitude

[12] Multi-factor models such as the Fama-French-three- and -four-factor model allow for the inclusion of more factors in addition to the market return. In the case of consumer mindset metrics it could for example be useful to inlcude factors such as market concentration or industry advertising intensity.

responsiveness dominates time-specific dynamics (Hanssens et al. 2014). Second, all brands within a market are affected by structural changes in market demand or consumer preferences, technological advances, and other external market trends. Market brand metrics entail industry-wide effects that affect all brands together and drive individual brand measures (Backhaus and Fischer 2016). For example, the overall image of banks heavily suffered in the aftermath of the great financial crisis. Thus, in case of a layoff announcement during this period of time, one would expect a negative brand strength and positive brand attention and dispersion return in comparison to prior levels before the financial crisis. However, these returns are rather driven by the positive relationship between market brand measures and the focal brand's strength, attention and dispersion, respectively. Hence, it is important to include market returns for a proper identification of effects. Furthermore, brand relevance differs significantly across different industries (Fischer, Völckner, and Sattler 2010). Consumer perceptions (which drive brand strength, brand attention, and brand rating dispersion) across markets are structurally different. Consequently, a market return factor can capture such effects. Following the market-adjusted model I use the average industry brand perceptions as benchmark market returns.

Estimation window. Given the selection of a performance forecast model, the estimation window needs to be defined. The selection of an appropriate estimation window is crucial for the proper estimation of expectations (MacKinlay 1997). However, there is no uniform rule that can be applied for choosing the correct window length. With regard to my data sample I define the estimation window as the three months prior to the event (=60 days), which should provide sufficient observations for estimation. I also provide robustness checks with respect to longer estimation windows in Appendix D (see robustness section).

It seems rather implausible that leakage or insider information with respect to consumer perception exists on a general basis. However, in line with the traditional event study approach, I account for possible leakage and exclude observations immediately before the event and define the estimation window as [-70; -10].

Aggregation of abnormal returns. In order to draw inferences concerning statistical significance and average effect strength of abnormal returns it is necessary to aggregate returns over events and over time in the event window. In line with financial event studies aggregation across the sample of *N* events is straightforward and the average abnormal return *AAR* of performance metric *k* on day *t* is calculated as

$$AAR_{k,t} = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \ . \tag{9}$$

The average abnormal returns are then cumulated over the length of the event window [t_1;t_2]

$$CAAR_k\left[t_1,t_2\right] = \sum_{\tau=t_1}^{t_2} AAR_{\tau} \ . \tag{10}$$

Since it is unclear how efficient consumer process new information on firms and brands and also how quickly consumer mindset metrics pick up these changes, I leave the length of the event window as an empirical issue. However, I define the maximum window length to be two weeks after the announcement (=10 days). Furthermore, I account for the effect that the diffusion of information through online media has taken place shortly before the first offline media publication. Therefore, the event window includes the day prior to the announcement. Robustness checks including up to three day prior to the announcement support the assumption that there is no further leakage (again see Appendix D). Consequently, the event window length varies running from the minimum of one day [-1,-1] to the maximum of 12 days [-1,10].

5. Significance Testing

Hypothesis testing is an integral part of event studies to assess whether the abnormal effects pertaining to the sample of events are significantly different from zero (Corrado 2011). That is, they are not the results of pure chance. The choice of the appropriate test statistic should be informed by the research setting and the statistical issues the analyzed data holds. Specifically, event-date clustering has been identified as central problem leading to (1) bias from event-induced volatility changes and (2) cross-sectional correlation of abnormal returns (Corrado 2011). In the application to marketing-related performance measures neither of both presumptions can be refuted or completely ruled out. Hence, in this study I apply parametric and nonparametric tests in order to protect against false inferences. Specifically, I apply the Patell-test (Patell 1967), the BMP-test (Boehmer, Musumeci, and Poulsen 1991) and the nonparametric sign test proposed by Cowan (1992) with respect to the cumulated abnormal returns of my three brand metrics.[13]

6. Cross-sectional Moderator Analysis

The variation in abnormal returns across single events cannot be explained by testing only for the significance of abnormal returns (McWilliams and Siegel 1997). Therefore, event studies typically apply a second stage multivariate cross-sectional regression (e.g., Wiles, Morgan, and Rego 2009, Homburg, Vollmayr, and Hahn 2014). The estimated cumulative abnormal returns of the brand strength (CAR^{BS}), brand attention (CAR^{BA}), and brand rating dispersion brand attention (CAR^{BD}) of each event j are the dependent variables in my moderator analysis:

$$CAR_j^k\left[t_1,t_2\right]=\delta_0^k+\sum_n\gamma_n^kL_n+\sum_n\omega_n^kF_n+\upsilon^k \tag{11}$$

with k=(BS,BA,BD) and where L_n represents layoff-specific characteristics (strategic motive, layoff size, timing, and country of layoff) and F_n are the firm-specific characteristics (prior brand strength, prior brand attention, layoff history, country of origin, and industry). The parameters γ^{BS},γ^{BA} and ω^{BS},ω^{BA} are the respective effects of layoff- and firm-specific characteristics on brand strength and brand attention returns. The parameters δ^{BS} and δ^{BA} are

[13] See Corrado (2011) for a detailed discussion of tests and test-statistics.

intercepts and υ^{BS} and υ^{BA} denote the error terms.[14] The 179 layoff announcements determine the sample size of these regressions.

5 Results

5.1 Assessing the Model Fit

Comparing the explanatory power and forecast efficiency of my return models to traditional financial event studies is not trivial because the necessary information is usually not reported by authors. Therefore, I assess the model fit and statistical characteristics of my approach to validate the application of the event study methodology to consumer mindset metrics. The market model regressions within the estimation window are on average highly significant across all 179 events (mean F-value = 7.57, $p<.01$). Furthermore, the error terms of the regressions as well as the absolute returns pass test for being normally distributed. In addition, all three expectations models offer robust results with respect to the significance and size of abnormal returns during the event window. In conclusion, my results support the validity of the event study application to consumer mindset metrics.

5.2 Layoff Effects on Consumer Mindsets

Table 4 presents the average cumulative average abnormal returns (*CAAR*s) in the investigated mindset metrics based on the constant mean return model for all 179 layoff announcements and different time intervals. Table 5 and 6 present the results for the mean-adjusted model and the market return model, respectively. Figure 4 illustrates the average abnormal returns by day (daily and cumulative) for each of the three consumer mindset metrics across the sample. In the following, I discuss the market return model results for each consumer mindset metric in turn (Table 6).

[14] To account for measurement error in the abnormal returs and heteroskedastic errors, I apply weighted-least-squares regression and weigth each observation with the inverse of the abnormal returns' variance from the estimation window.

Brand attention effects. Consistent with Hypothesis 1 the abnormal returns for brand attention are positive on average. However, *CAAR*s are significant only between day 5 to 8 with respect to all three test statistics ($CAAR^{BA}$[-1;5], = .50%, p < .05 for all tests). Interestingly, event windows after day 8 do not show any significant *CAAR*s. This result could indicate that the attention affect is rather a pulsing effect that diminishes after a couple of days. The largest cumulated effect on day 5 (.50%) is comparable in size to the negative effect on brand strength.

Brand strength effects. I find significant negative *CAAR*s with respect to brand strength from the day after the announcement [-1;1]. Until day 5, the results remain consistent showing increasing abnormal negative returns at high significance levels for all three tests (Patell-, BMH-, and Sign-test, p < .01). Hence, I find strong support for Hypothesis 2. Note that the effects of layoff announcements on brand strength are strongest for the one-week event window ($CAAR^{BS}$[-1;5] = -.53%, p < .01 for all tests). These results are consistent with prior findings on corporate reputation and customer satisfaction research (e.g., Love and Kraatz 2009, Habel and Klarmann 2015). The new information takes about a week to be fully reflected in the brand strength measure.

Brand rating dispersion effects. Surprisingly, I do not find any significant effects with regard to the abnormal returns in brand rating dispersion which would support Hypothesis 3. *CAAR*s for brand rating dispersion fluctuate from positive ($CAAR^{BD}$[-1;1], = .07%) to negative ($CAAR^{BD}$[-1;3], = -.35%) and seem to follow a random process. This is supported by the graphical illustration of *AAR*s and *CAA*Rs over time in Figure 4. Hence, the spread between brand haters and lovers does not seem to increase or decrease after a layoff announcements

5.3 **Explaining the Variance in Cumulative Abnormal Returns**

Table 7 presents the results from the cross-sectional regression of moderating variables on cumulated abnormal return (*CAR*s) for brand strength and brand attention for the event window [-1;5]. I choose this window because the size of the returns is largest both for brand strength and brand attention within this time period. Please note that there are no significant returns identified for brand rating dispersion and results of the moderator analysis do not provide any further insights. Hence, I only report these results in Appendix C. I also could not detect any industry effects. As a consequence, because model fit did not change significantly, industry dummies are not included in the final regression model. In the following, I will discuss the most interesting findings from the moderation analysis for brand strength and brand attention.

Brand attention. The cross-sectional regression with respect to brand attention only offers limited insights with an model fit ($R^2 = .09$) and only two significant effects ($p < .05$). First, when layoffs are communicated to be caused by financial distress, consumer's attention is higher than in a proactive situation ($\gamma_1^{BA} = .170$; $p < .05$). Second, the findings suggest that firms with previous high brand attention also receive more attention by consumers in the case of a layoff announcement ($\omega_2^{BA} = .166$; $p < .01$).

Table 4: Event Study Results With Respect to Consumer Mindset Metrics (Mean Model)

A: Constant mean return model *(estimation window = 60 days)*												
	Brand attention				Brand strength				Brand rating dispersion			
Day	CAAR [-1,x]	Pos:Neg[1]	Patell-test	BMP-test	CAAR [-1,x]	Pos:Neg[1]	Patell-test	BMP-test	CAAR [-1,x]	Pos:Neg[1]	Patell-test	BMP-test
-1	-.19%	83:96	.43	-1.66 **	-.05%	94:85	-1.09	-.70	-.21%	84:95	.32	.19
0	-.14%	83:96	-1.73 **	-.78	-.15%	80:99*	-.85	-1.93 **	-.33%	85:94	.20	-.15
1	-.16%	83:96	-.74	-.67	-.30%	74:105**	-2.32 **	-3.19 ***	.21%	87:92	-.11	.78
2	.04%	81:98	-.59	.51	-.46%	70:109***	-3.69 ***	-4.26 ***	-.21%	86:93	.41	.51
3	.25%	93:86	.47	1.47 *	-.49%	66:113***	-4.97 ***	-4.17 ***	-.14%	95:84	.24	.58
4	.42%	91:88	1.55 *	1.31 *	-.57%	65:114***	-4.64 ***	-3.91 ***	.79%	100:79*	.26	.71
5	.49%	106:73**	2.07 **	2.54 ***	-.55%	69:110***	-4.77 ***	-3.99 ***	.82%	100:79*	.80	2.54 ***
6	.53%	101:78***	2.25 **	2.66 ***	-.49%	76:103**	-4.21 ***	-3.34 ***	-.18%	87:92	.94	.46
7	.43%	93:86	2.31 **	2.29 **	-.37%	83:96	-3.38 ***	-2.44 ***	.27%	97:82	.16	1.49 *
8	.25%	93:86	1.83 **	1.39 *	-.30%	87:92	-2.30 **	-1.98 **	.12%	95:84	.54	.81
9	.19%	90:89	1.04	1.08	-.35%	78:101**	-1.71 **	-2.34 ***	.56%	100:79*	.26	1.81 **
10	.13%	91:88	1.04	.79	-.32%	80:99*	-1.71 **	-1.94 **	.23%	86:93	.26	1.06

Notes: *** p < .01; ** p < .05; * p < .1. Two-sided tests. BMP = Boehmer-Musumeci-Poulsen test. CAAR = Cumulated average abnormal return.
[1)] Significance based on sign test proposed by Cowan (1991).

Table 5: Event Study Results With Respect to Consumer Mindset Metrics (Market-adjusted Model)

B: Market-adjusted return model *(estimation window = 60 days)*

	Brand attention				Brand strength				Brand rating dispersion			
Day	CAAR [-1,x]	Pos:Neg[1]	Patell-test	BMP-test	CAAR [-1,x]	Pos:Neg[1]	Patell-test	BMP-test	CAAR [-1,x]	Pos:Neg[1]	Patell-test	BMP-test
-1	-.16%	89:90	0.70	-1.68 **	-.02%	91:88	-0.34	-0.74	-.54%	78:101**	-0.13	-0.75
0	-.11%	82:97	-0.87	-0.57	-.13%	80:99*	-0.30	-2.18 **	-.58%	85:94	-0.71	-1.10
1	-.10%	86:93	-0.28	-0.45	-.26%	72:107***	-0.93	-3.13 ***	.07%	84:95	-0.81	0.32
2	.13%	89:90	-0.22	1.01	-.40%	72:107***	-1.24	-3.86 ***	-.39%	84:95	0.17	-0.40
3	.33%	99:80*	0.49	1.94 **	-.46%	70:109***	-1.64 *	-3.63 ***	-.52%	82:97	-0.20	-0.71
4	.51%	104:75**	1.11	1.70 **	-.53%	66:113***	-1.57 *	-3.45 ***	.00%	85:94	-0.32	-0.63
5	.56%	103:76**	1.39 *	2.97 ***	-.53%	61:118***	-1.67 **	-3.84 ***	.22%	98:81	0.05	0.89
6	.62%	102:77**	1.36 *	3.19 ***	-.46%	77:102**	-1.50 *	-3.11 ***	-.47%	86:93	0.34	-0.86
7	.51%	97:82	1.46 *	2.72 ***	-.36%	82:97	-1.21	-2.61 ***	-.17%	95:84	-0.29	0.01
8	.32%	96:83	1.14	2.06 **	-.30%	83:96	-0.91	-2.22 **	-.28%	81:98	0.00	-0.52
9	.29%	96:83	0.79	2.20 **	-.32%	79:100*	-0.69	-2.46 ***	-.01%	91:88	-0.18	0.30
10	.25%	91:88	0.79	2.10 **	-.28%	82:97	-0.69	-1.86 **	-.36%	81:98	-0.18	-0.43

Notes: *** p < .01; ** p < .05; * p < .1. Two-sided tests. BMP = Boehmer-Musumeci-Poulsen test. CAAR = Cumulated average abnormal return.
1) Significance based on sign test proposed by Cowan (1991).

Table 6: Event Study Results With Respect to Consumer Mindset Metrics (Market Model)

C: Market return model *(estimation window = 60 days)*												
	Brand attention				Brand strength				Brand rating dispersion			
Day	CAAR [-1,x]	Pos:Neg[1]	Patell-test	BMP-test	CAAR [-1,x]	Pos:Neg[1]	Patell-test	BMP-test	CAAR [-1,x]	Pos:Neg[1]	Patell-test	BMP-test
-1	-.20%	89:90	.37	-1.26	-.04%	92:87	-1.06	-.65	-.52%	81:98	.01	-.56
0	-.13%	84:95	-1.28	-.65	-.14%	80:99*	-.72	-1.95 **	-.64%	82:97	-.55	-1.11
1	-.15%	82:97	-.64	-.54	-.26%	70:109***	-2.17 **	-3.13 ***	.07%	87:92	-.81	.29
2	.08%	85:94	-.49	.70	-.39%	69:110***	-3.36 ***	-3.91 ***	-.35%	84:95	.16	-.25
3	.27%	90:89	.65	1.31 *	-.46%	66:113***	-4.34 ***	-4.01 ***	-.35%	85:94	-.12	-.19
4	.43%	97:82	1.40 *	1.14	-.55%	66:113***	-4.35 ***	-3.83 ***	.09%	91:88	-.08	-.05
5	.50%	101:78**	1.74 **	2.30 **	-.53%	67:112***	-4.49 ***	-3.95 ***	.23%	98:81	.21	1.06
6	.52%	101:78**	2.08 **	2.55 ***	-.48%	83:96	-4.02 ***	-3.29 ***	-.26%	90:89	.41	-.17
7	.42%	93:86	2.29 **	2.18 **	-.40%	81:98	-3.25 ***	-2.68 ***	-.10%	92:87	-.06	.24
8	.28%	96:83	1.78 **	1.41 *	-.35%	84:95	-2.41 ***	-2.35 ***	-.25%	83:96	.09	-.31
9	.20%	93:86	1.05	1.07	-.38%	77:102**	-1.93 **	-2.60 ***	.05%	87:92	-.11	.55
10	.16%	87:92	1.05	.60	-.35%	78:101**	-1.93 **	-2.15 **	-.24%	85:94	-.11	.04

Notes: *** p < .01; ** p < .05; * p < .1. Two-sided tests. BMP = Boehmer-Musumeci-Poulsen test. CAAR = Cumulated average abnormal return.
[1)] Significance based on sign test proposed by Cowan (1991).

Table 7: Cross-sectional Analysis of Moderator Effects (WLS-Regression)

		Brand attention				Brand strength			
		Expected sign	Standardized coefficient		(Standard error)	Expected sign	Standardized coefficient		(Standard error)
Intercept		+/-	-.009		(.008)	+/-	.003		(.005)
Layoff-specific moderators									
Strategic motive	*Proactive (base)*		-				-		
	Reactive	+/-	.170	**	(.005)	+	.105	*	(.003)
Layoff size		+	-.036		($3.3x10^{-7}$)	-	-.254	***	($2.0x10^{-7}$)
Timing of announcement	*After financial crisis*[1]		-				-		
	During financial crisis[2]	+/-	.147	*	(.006)	+	.130	*	(.004)
Country of announcement	*United States (base)*		-				-		
	Germany	+/-	-.117		(.005)	-	-.200	**	(.003)
Firm-specific moderators									
Prior brand strength		+	-.064		($1.2x10^{-4}$)	+	.177	***	($7.2x10^{-5}$)
Prior brand attention		+	.166	**	($2.5x10^{-4}$)	+/-	-.160	**	($1.5x10^{-4}$)
Layoff history		+	.009		(.003)	-	-.044		(.002)
Country of origin	*Domestic (base)*								
	Foreign	+	.061		(.005)	-	-.008		(.003)
R2			*.09*				*.17*		
F-Statistic			*2.15*	**			*4.36*	***	
N			*179*				*179*		

Notes: Expected returns are based on the market-return model (c); * p<.1, ** p<0.05, *** p<0.01. Tests are one-sided if clear directional effects are expected, two-sided if not. Standard errors in parentheses. WLS regression, weights: standard deviation of returns in estimation window.
[1)]After financial crisis: 2010-2012; [2)] During financial crisis: 2008-2009.

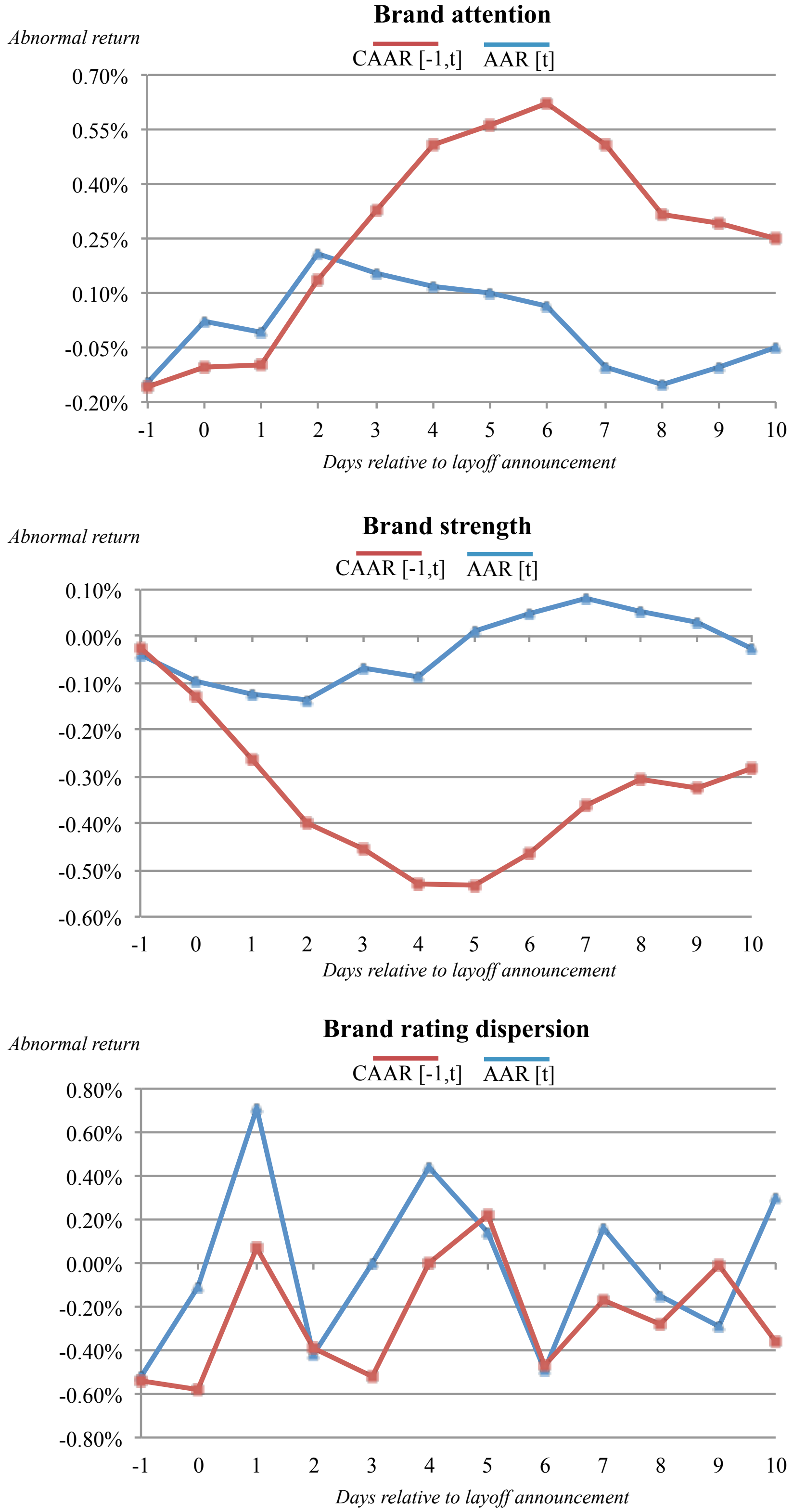
Brand strength. Consistent with my expectations I find strong support for differences in *CAR*s depending on the size of the layoff. The more employees are affected by a downsizing initiative the stronger is the negative effect on consumers' brand evaluation ($\gamma_2^{BS} = -.254$; $p < .01$). Prior brand strength reduces the negative impact of the layoff announcement whereas prior brand attention intensifies the negative effect ($\omega_1^{BS} = .177$; $p < .01$; and $\omega_2^{BS} = -.160$; $p < .05$). Furthermore, differences across cultures exist. Specifically, German consumers tend to punish firms more for laying off workforce ($\gamma_4^{BS} = -.200$; $p < .05$). Surprisingly, it seems that it does not matter whether the announcing firm is domestic or foreign or which strategic motive the company owns.

5.4 **Robustness Checks**

I checked the robustness of my results in several ways (see Appendix D for details). First, I used a 100 day estimation window for the mean return and the market return model. Results are consistent but the sample size of layoff announcements is reduced significantly which limits the application of cross-sectional regression in the second stage. I also estimated effects in the dependent variables (brand attention, brand strength, and brand rating dispersion) using alternative estimation techniques instead of the outlined return specifications (daily changes, relative changes to the market, absolute values).[15] Again, the results are on average stable and robust with respect to the return model. Finally, I estimated cross-sectional regressions for different event windows. None of these analyses suggest any different conclusions.

[15] Results with respect to alternative estimation techniques can be received on request from the author.

Figure 4: Average Abnormal and Cumulated Average Abnormal Returns For Mindset Metrics (Market-Model)



Note: CAAR = cumulative average abnormal return, AAR = average abnormal return

6 Discussion

6.1 Conclusion

This study generates new insights with respect to the effects of layoff announcements on consumers. Overall, the findings suggest that consumers indeed notice the announcement of layoffs and that firm's need to incorporate such effects into their decision making. The results reveal a significant effect on brand attention and brand strength. Surprisingly, no effects can be detected with respect to brand rating dispersion. Apparently, layoff announcements do not polarize enough between consumers to drive heterogeneity in brand evaluations. That is, consumers perceive layoffs similar and do not disagree about the evaluation of layoff announcements.

The effects on brand strength and brand attention are asymmetric, thus they support my Hypotheses 1 and 2. Layoff announcements increase brand attention but weaken brand strength. This finding is consistent with prior literature that negative news raise attention that might be valued by a firm (Berger, Sorensen, and Rasmussen 2010). However, the effect of brand attention diminishes after about a week, whereas the effect on brand strength does not. This implies that the overall effect of layoff announcements is especially driven by the negative effect in brand strength.

Furthermore, layoff and firm characteristics can be identified as key drivers of the announcement effect on brand attention and brand strength. There is higher brand attention in cases when layoffs are communicated to be caused by financial distress. This could be due to the fact that firms in financial distress (strategic motive) might generally receive more attention which is only triggered by the layoff itself. Moreover, I find that firms with high previous brand attention also receive more attention by consumers in the case of a layoff announcement. This finding contradicts prior research that suggests that less known brands gain relatively more attention from news (Berger, Sorensen, and Rasmussen 2010).

With respect to brand strength effects, I find that consistent with prior literature strong brands prior to the announcement serve as a buffer in case negative news about downsizing is covered in the media (Backhaus and Fischer 2016). Interestingly, German consumers react more negatively to layoff announcements than U.S. consumers. Although these results are in line with my expectations, they offer new explanations for different investor reactions across countries (Lee 1997). Although, reactive layoff announcements gain more attention by consumers, surprisingly, the type of layoff does not seem to influence the effects on brand strength. When firms proactively downsize they are not punished more by consumers than in situations of financial distress.

6.2 **Implications**

This study has implications for researchers and practitioners. Layoff initiatives usually aim to increase operational efficiency but short-term efficiency gains might be set off by negative effects on e.g., employee satisfaction and service quality (De Meuse et al. 2004). Therefore, in this study I provide insights into real-life layoff announcement effects on consumer mindset metrics and reveals asymmetric effects on brand strength and brand attention. This implies deferred negative financial performance effects (Hanssens et al 2014). I do not claim that every layoff has a severe negative effect on consumer brand perception but managers should be alert of a potential brand damage effect when announcing layoffs. From a practitioner's perspective, my results are thus valuable because they help understand better which announcements when and where have the potential to involve significant negative effects on consumers and ultimately firm performance. This enables managers to incorporate brand effects into their consideration set to make better decisions.

Furthermore, my study provides an important insight: although "hidden costs" of downsizing regarding employees, consumers, and brands are difficult to measure or estimate, investors should anticipate such effects. Hence, the results can guide investors to better forecast stock market reactions to layoff announcements and also help when evaluating the costs and benefits from downsizing initiatives.

Moreover, Hanssens et al. 2014 note that attitudinal metrics have potential, stickiness, and responsiveness to marketing. My study underpins the usefulness of disaggregate consumer mindset metrics and offers an additional perspective in studying the effect of non-marketing related firm actions on consumers. Market research companies such as YouGov have recently begun to collect, track, and process such data. Managers should be aware to use these new data as it is shown to serve as useful alternative indicators for changes in brand and financial performance of firms. Managers can make use this new "normal" for their advantage in order to build competitive advantages.

Finally, this study also outlines and discusses the necessary conditions and assumptions for extending the event study methodology to consumer mindset metrics. I provide a step-by-step framework for the application of an extended event study to different performance metrics. Particular, I discuss the critical steps of modeling expectations in order to estimate abnormal changes in the dependent variable as well as the proper identification of confounding events. The results indicate that event studies are indeed a valuable tool in analyzing the effects and implications from specific, nonrecurring events on highly frequent consumer data. Thus, the extended framework for event study analysis can serve as a starting point for future research. It should guide researches through the necessary steps for transferring and conducting event studies in very different settings besides calculating abnormal stock returns. Although it is probably not possible to provide a fully comprehensive set of possible events with a confounding character, Figure 3 can serve as base for future event studies with marketing-related performance measures. The discussion of a conceptual definition of confounding events should also enrich academic discussion within this direction.

References Paper II

Aaker, Jennifer (1997), "Dimensions of Brand Personality," *Journal of Marketing Research*, 34 (3), 347-356.

Agrawal, Jagdish and Wagner A. Kamakura (1995), "The Economic Worth of Celebrity Endorsers: An Event Study Analysis," *Journal of Marketing,* 59 (3), 56-62.

Ahluwalia, Rohini (2002), "How Prevalent Is the Negativity Effect in Consumer Environments?," *Journal of Consumer Research*, 29 (2), 270-79.

Ahluwalia, Rohini, Robert E. Burnkrant, and H. Rao Unnava (2000), "Consumer Response to Negative Publicity: The Moderating Role of Commitment," *Journal of Consumer Research*, 37 (2), 203-214.

Amabile, Teresa M. and Regina Conti (1999), "Changes in the work environment for creativity during downsizing," *Academy of Management Journal*, 42 (6), 630-640.

Backhaus, Max and Marc Fischer (2016), "Brand damage from product harm and corporate social irresponsibility – How deep and how long?" *MSI Working Paper Series*, forthcoming.

Bhattarcharya, C.B. and Sankar Sen (2003), "Consumer-Company Identification: A Framework for Understanding Consumers' Relationships with Companies," *Journal of Marketing*, 76 (2), 76-88.

Berger, Jonah, Alan T. Sorensen, and Scott J. Rasmussen (2010), "Positive effects of negative publicity: When negative reviews increase sales," *Marketing Science,* 29 (5), 815-827.

Brockner, Joel, Mary Konovsky, Rochelle Cooper-Schneider, Robert Folger, Christopher Martin, and Robert J. Bies (1994), "Interactive Effects of Procedural Justice and Outcome Negativity on Victims and Survivors of Job Loss," *Academy of Management Journal*, 27 (2), 397-409.

Brown, Tom J. and Peter A. Dacin (1997), "The Company and The Product: Corporate Associations and Consumer Product Responses, *Journal of Marketing*, 61 (1), 68-84.

Brown, Stephen J. and Jerold B. Warner (1985), "Using Daily Stock Returns: The Case of Event Studies," *Journal of Financial Economics*, 14 (1), 3-31.

Chalos, Peter and Charles J. P. Chen (2002), "Employee Downsizing Strategies: Market Reaction and Post announcement Financial Performance," *Journal of Business Finance & Accounting*, 29 (5-6), 847-870.

Chen, Peter, Vikas Mehrotra, Ranjini Sivakumar, and Wayne W. Yu (2001), "Layoffs, Shareholders' Wealth, and Corporate Performance," *Journal of Empirical Finance*, 8 (2), 171-199.

Chen, Yubo, Shankar Ganesan, and Yong Liu (2009), “Does a Firm's Product-Recall Strategy Affect Its Financial Value? An Examination of Strategic Alternatives During Product-Harm Crises,” *Journal of Marketing*, 73 (6), 214-226.

Corrado, Charles J. (2011), “Event Studies: A Methodology Review,” *Accounting & Finance,* 51 (1), 207-234.

Cowan, Arnold Richard (1992), “Nonparametric Event Study Tests,” *Review of Quantitative Finance and Accounting,* 2 (4), 343-358.

Datta, Deepak, K., James P. Guthrie, Dynah Basuil, and Alankrita Pandey (2010), “Causes and Effects of Employee Downsizing: A Review and Synthesis,” *Journal of Management*, 36 (1), 281-348.

De Meuse, Kenneth P., Thomas J. Bergmann, Paul A. Vanderheiden and Catherine E. Roraff (2004), “New Evidence Regarding Organizational Downsizing and a Firm’s Financial Performance: A Long-term Analysis,” *Journal of Managerial Issues*, 16 (2), 155-177.

Fama, Eugene F., et al. (1969), “The Adjustment of Stock Prices to New Information,” *International Economic Review*, 10 (1), 1-21.

Fischer, Marc, Franziska Völckner, and Henrik Sattler (2010), “How Important Are Brands? A Cross-Category, Cross-country Study,” *Journal of Marketing Research*, 47 (5), 823-839.

Flanagan, David J. and K. C. O’Shaughnessy (2005), “The Effect of Layoffs on Firm Reputation, *Journal of Management*,” 31 (3), 445-463.

Fornell, Claes, Sunil Mithas, Forrest V. Morgeson, and M.S. Krishnan (2006), “Customer Satisfaction and Stock Prices: High Returns, Low Risk,” *Journal of Marketing*, 70 (1), 3-14.

Freeman, Sarah J. and Kim S. Cameron (1993), “Organizational Downsizing: A Convergence and Reorientation Framework,” *Organization Science*, 4, 10-29.

Friebel, Guido and Matthias Heinz (2014), “Media Slant Against Foreign Owners: Downsizing,” *Journal of Public Economics*, 120, 97-106.

Gao, Haibing, Jinhong Xie, Qi Wang, and Kenneth C. Wilbur (2015), “Should Ad Spending Increase or Decrease Before a Recall Announcement? The Marketing–Finance Interface in Product-Harm Crisis Management,” *Journal of Marketing*, 79 (5), 80-99.

Geyskens, Inge, Katrijn Gielens, and Marnik G. Dekimpe (2002), “The Market Valuation of Internet Channel Additions,” *Journal of Marketing,* 66 (2), 102-119.

Habel, Johannes and Martin Klarmann (2015), “Customer Reactions to Downsizing: When and How is Satisfaction Affected?” *Journal of the Academy of Marketing Science*, 43 (6), 768-789.

Hanssens, Dominique M., Koen H. Pauwels, Shuba Srinivasan, Marc Vanhuele, and Gokhan Yildirim (2014), “Consumer Attitude Metrics for Guiding Marketing Mix Decisions,” *Marketing Science*, 33 (4), 534-550.

Hofstede, Geert (2003), *Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations*, 2nd ed. Thousand Oaks: Sage.

Homburg, Christian, Martin Klarmann, and Sabine Staritz (2012), "Customer Uncertainty Following Downsizing: The Effects of Extent of Downsizing and Open Communication", *Journal of Marketing*, 76 (3), 112-129.

Homburg Christian, Josef Vollmayr, and Alexander Hahn (2014), "Firm Value Creation Through Major Channel Expansions: Evidence from an Event Study in the United States, Germany, and China," *Journal of Marketing*, 78 (3), 38-61.

Katsikeas, Constantine S., Neil A. Morgan, Leonidas C. Leonidou, and G. Tomas M. Hult (2016), "Assessing Performance Outcomes in Marketing," *Journal of Marketing*, 80 (2), 1-20.

Keller, Kevin Lane (1993), "Conceptualizing, Measuring, and Managing Customer-based Brand Equity," *Journal of Marketing*, 57 (1), 1-22.

Keller, Kevin Lane (2008), *Strategic Brand Management*, 3rd ed. Englewood Cliffs: Prentice Hall.

Kumar, V. and Werner Reinartz (2016), "Creating Enduring Customer Value," *Journal of Marketing*, forthcoming.

Lee, Peggy M. (1997), "A Comparative Analysis of Layoff Announcememtns and Stock Price Reactions in the United States and Japan", *Strategic Management Journal*, 18 (11), 879-894.

Levy, Sidney J. (1959), "Symbols for Sale," *Harvard Business Review*, 37, 117–24.

Lewin, Jeffrey E., Wim Biemans, and Wolfgang Ulaga (2010), "Firm Downsizing and Satisfaction Among United States and European Customers," *Journal of Business Research*, 63 (7), 697-706.

Long, Heather (2016), "America's Top 10 Job-Killing Companies", CNN.org, (accessed October 2, 2016), available at http://money.cnn.com/2016/05/15/news/economy/america-job-killing-companies/

Love, E. Geoffrey and Matthew Kratz (2009), "Character, Conformity, or the Bottom Line? How and Why Downsizing Affected Corporate Reputation, *Academy of Management Journal*, 52 (2), 314-335.

Luo, Xueming, Raithel, Sascha, and Michael Wiles (2013), "The Impact of Brand Dispersion on Firm Value," *Journal of Marketing Research*, 50 (3), 399-415.

Lord, Charles G., Lee Ross, and Mark R. Lepper (1979), "Biased assimilation and attitude polarization: The effects of prior theories on subsequently considered evidence," *Journal of Personality and Social Psychology*, 37 (11), 2098–2109.

MacKinlay, A. Craig (1997), "Event Studies in Economics and Finance," *Journal of Economic Literature*, 35 1), 13–39.

McWilliams, Abagail and Donald Siegel (1997), “Event Studies in Management Research: Theoretical and Empirical Issues”, *The Acadamy of Management Journal*, 40 (3), 626-57.

Mishra, Aneil K. and Karen E. Mishra (1994), “The Role of Mutual Trust in Effective Downsizing Strategies” *Human Resource Management*, 33 (2), 261-279.

Patel, James M. (1976), “Corporate Forecasts of Earnings Per Share and Stock Price Behavior: Empirical Tests,” *Journal of Accounting Research*, 14 (2), 246-276.

Sandman, Peter M. and Mary Paden (1979), “At Three Mile Island,” *Columbia Journalism Review*, 18 (2), 1-43.

Stahl, Florian, Mark Heitmann, Donald R. Lehmann, and Scott A. Neslin (2012), “The Impact of Brand Equity on Customer Acquisition, Retention, and Profit Margin,” *Journal of Marketing*, 76 (4), 44-63.

Subramony, Mahesh, and Brooks C. Holtom (2012), "The Long-term Influence of Service Employee Attrition on Customer Outcomes and Profits," *Journal of Service Research,* 15 (4), 460-473.

Swaminathan, Vanitha, and Christine Moorman (2009), "Marketing Alliances, Firm Networks, and Firm Value Creation," *Journal of Marketing,* 73 (5), 52-69.

U.S. Bureau of Labor Statistics (2016), “Mass Layoff Statistics”, (accessed October 2, 2016), available at http://www.bls.gov/mls/

Wiles, Michael A., Neil A. Morgan, and Lopo L. Rego (2012), “The Effect of Brand Acquisitions and Disposal on Stock Returns,” *Journal of Marketing*, 76 (1), 38-38.

Williams, Paul, M. Sajid Khan, and Earl Naumann (2011), “Customer Dissatisfaction and Defection: The Hidden Costs of Downsizing”, *Industrial Marketing Management*, 40 (3), 405-413.

Zautra, Alex J., Glenn G. Affleck, Howard Tennen, John W. Reich, and Mary C. Davis (2005), “Dynamic Approaches to Emotions and Stress in Everyday Life,” *Journal of Personality*, 73 (6), 1511-38.

Zyglidopoulos, Stelios (2005), “The Impact of Downsizing on Corporate Reputation,” British *Journal of Management*, 16, 253-259.

Appendix Paper II

Appendix A: Details on the YouGov Brand Metric Measures

In the following, I describe the data collection YouGov used from 2008-2012 to collect brand attention and brand strength (on which also brand rating dispersion is based) information. Starting in 2013 the company applies a modified methodology with an expanded the set of items.

YouGov's BrandIndex is a daily measure of brand strength among the public, tracking many brands across multiple consumer sectors simultaneously. For the German market, YouGov monitors about 600 brands in 12 industry sectors, which cover the bandwidth of B2C industries by surveying approximately 2,000 consumers (panel size of 170,000) daily. For the U.S. market the company covers over 1,000 brands and 5,000 daily interviews.

The data collection of YouGov can be described as follows: For each item a minimum of 100 respondents per day are randomly drawn from the panel and provided with a set of up to 25 brands for a pre-selected industry. To reduce common method bias respondents evaluate only one brand item per industry per enquiry. First, respondents select those brands (per click) for which they agree with the positive statement of the brand item (e.g., good brand quality). Then, they select those brands for which they agree with the negative statement of the brand item (e.g., poor brand quality). The aggregate raw brand strength measure (YouGov BrandIndex) is calculated by counting the number of respondents who agree with the six positive statements (items) and the number of respondents who agree with the six negative statements (items) divided by the total number of respondents (= number of positive + negative + neutral respondents) multiplied by 100. As a consequence, the YouGov BrandIndex brand strength measure is a ratio-scaled variable and lies within the range of -100 to +100. The brand attention metric is calculated by summing up all positive and negative responses divided by the total number of respondents (= number of positive + negative + neutral responses).

The collection procedure yields about 100 daily responses for each of the seven brand items. To ensure representativeness individual sampling weights are applied to correct for variations in the probability selection of respondents. Although panelists might be re-invited after a period of two weeks, they will be blocked for the respective sector and brand item they have answered before for a period of at least two months. This is important to eliminate repeated measurement as a source for demand effects and serial correlation in brand perceptions. Brand competition effects are also controlled for because respondents rate the competing brands within one sector simultaneously.

The BrandIndex consists of six items: perceived brand quality, brand value, brand satisfaction, brand recommendation, brand identification, and brand overall impression. Additionally, YouGov also asks respondents with respect to a seventh item: brand attention. Table A1 provides details on the exact question for each item.

Table A1
ITEMS FOR MEASURING BRAND ATTENTION AND BRAND STRENGTH AND BRAND RATING DISPERSION (YOUGOV's BRANDINDEX)

Dimension	*Questions*
Brand attention	About which of the following brands have you recently heard anything positive or negative either through media news, advertising, or word-of-mouth?
Brand quality	Which of the following brands do you think stand for good quality? Now, which of the following brands stand for poor quality?
Brand value	Which of the following brands do you think provide good value for money (or you would be willing to invest parts of your spare time)? † Now, which of the following brands do you think provide poor value for money (or you would be willing to invest parts of your spare time)? ††
Brand satisfaction	Choose all brands you are satisfied with or for which you believe you would be satisfied if you were a customer? Choose all brands you are dissatisfied with or for which you believe you would be dissatisfied if you were a customer?
Brand recommendation	Which of the following brands would you recommend to a friend or colleague? And which of the following brands would you recommend a friend or colleague to avoid?
Brand identification	Which of the following brands would you be proud of to work for or to be associated with? ††† Now, which of the following brands would you be embarrassed to work for or be associated with? †††
Brand overall impression	Overall, of which of the following brands do you have a positive impression? Now, of which of the following brands do you have an overall negative impression?

Note: Additional explanations provided to the respondent include:
† By that we don't mean "cheap," but that the brands offer a customer a lot in return for the price paid.
†† By that, we don't mean "expensive," but that the brands do not offer a customer much in return for the price paid.
††† Imagine you (or your friend) were applying for the same sort of role at the following brands that you currently have or would apply for.

Appendix B: Details on Layoff Announcement Data

The data collection process to identify layoff announcements in German and U.S. media involved a systematic 5-step approach:

1. In the first step I generated a list of keywords commonly used in news headlines and articles with regard to layoffs or downsizing initiatives. For this purpose, I conducted brainstorming sessions with a panel of experts and journalists. Also, I enriched the keyword list through the Google AdWords “Find related searches” function.
2. I then pre-tested the keywords (up to 60 keywords) on a random sample of ten a priori identified layoff announcements in order to reduce complexity and efficiency within the search algorithm. Based on the hit ratio of relevant articles and the total number of generated hits I excluded about 65% of all keywords.
3. Next, I conducted search queries in LexisNexis and additional news archives by connecting all brands available from the YouGov database with our keyword list and searched for hits within the headlines and lead paragraphs of articles in leading U.S. and German media outlets.
4. In a fourth step, two coders individually read all relevant articles and categorized crisis events with regard to the strategic motive and size of the layoff. Coding agreement across all variables was greater than 95%. Cases of non-agreement were decided by discussion.
5. Finally, in addition to the original layoff search, I double checked for possible confounding events for all detected layoff events within media articles, company reports, and news published through corporate webpages.

Table B1 presents the layoff events that are part of my empirical analysis. It shows the company brand name, country of layoff announcement, and when the announcement was first published.

Table B1
LAYOFF ANNOUNCEMENTS INCLUDED IN EMPIRICAL ANALYSIS

ID	Company Brand	Country	Date	continued….			
1	A&P	US	8/16/12	46	Deutsche Bank	GER	8/31/11
2	Adidas	GER	5/5/09	47	Deutsche Post	GER	6/5/09
3	Aetna	US	12/31/09	48	Disney Channel	US	6/7/11
4	Air France	US	9/4/09	49	e.on	GER	8/27/08
5	Air France	US	6/21/12	50	e.on	GER	11/23/10
6	AirFrance	GER	4/15/09	51	e.on	GER	8/1/11
7	AirFrance	GER	9/4/09	52	EA Games	GER	12/19/08
8	AirFrance	GER	6/25/10	53	EA Games	GER	11/10/09
9	AirFrance	GER	5/22/12	54	Ebay	GER	9/26/08
10	Alfa Romeo	GER	12/7/12	55	Ebay	GER	10/1/09
11	AMD	GER	12/31/08	56	EWE Energy	GER	1/27/12
12	American Airlines	US	6/11/09	57	EWE Telco	GER	1/27/12
13	American Airlines	US	2/2/12	58	FedEx	GER	2/11/09
14	American Airlines	US	9/18/12	59	Fiat	GER	12/7/12
15	American Apparel	US	9/4/09	60	Ford	GER	5/30/08
16	American Eagle	US	12/16/11	61	Friendscout	GER	6/22/12
17	American Eagle	US	3/22/12	62	Fujitsu	GER	11/28/08
18	American Express	US	1/25/11	63	Fujitsu	GER	8/31/09
19	AstraZeneca	US	12/7/11	64	Galeria Kaufhof	GER	10/6/08
20	AstraZeneca	US	6/13/12	65	Galeria Kaufhof	GER	7/17/09
21	Bank of America	US	8/19/11	66	Galeria Kaufhof	GER	6/18/10
22	Bank of America	US	9/12/11	67	Galeria Kaufhof	GER	4/20/12
23	Bank of America	US	5/1/12	68	Germanwings	GER	5/29/12
24	Bank of Scotland	GER	1/19/12	69	Helaba	GER	1/17/12
25	Bank of Scotland	GER	9/25/12	70	Hewlett-Packard	GER	9/16/08
26	Barclays Bank	GER	12/13/12	71	Hewlett-Packard	GER	5/20/09
27	Bayerische Landesbank	GER	6/18/08	72	Hewlett-Packard	GER	5/23/12
28	Bayerische Landesbank	GER	2/26/09	73	HP	US	6/2/10
29	BlackBerry	US	12/18/09	74	HP	US	5/24/12
30	BlackBerry	GER	6/17/11	75	HSBC	US	8/1/11
31	BP	GER	5/6/09	76	HTC	GER	7/25/12
32	Bristol-Myers Squibb	US	9/24/10	77	ING-DiBa	GER	7/1/09
33	British Airways	GER	10/7/09	78	ING-DiBa	GER	11/7/12
34	British Airways	GER	8/3/12	79	Intel	GER	1/22/09
35	Canon	GER	6/30/09	80	Johnson & Johnson	US	11/2/09
36	Chevron	US	3/9/10	81	Kaiser's	GER	6/30/10
37	Citroen	GER	11/21/08	82	Karstadt	GER	9/2/08
38	Citroen	GER	7/13/12	83	Karstadt	GER	7/17/12
39	Citroen	GER	12/12/12	84	KiK	GER	6/30/10
40	Commerzbank	GER	7/13/12	85	KLM	US	9/14/09
41	Continental	GER	5/5/10	86	KLM	US	6/21/12
42	Continental	GER	9/23/10	85	KLM	US	9/14/09
43	Deutsche Bahn	GER	3/13/09	86	KLM	US	6/21/12
44	Deutsche Bahn	GER	9/4/09	87	Kodak	US	9/10/12
45	Deutsche Bank	GER	10/21/10	88	L'Oréal	GER	2/18/09

ID	Company Brand	Country	Date	continued….			
89	Lexmark	US	8/29/12	135	Santander	GER	3/27/12
90	Lufthansa	GER	11/18/08	136	Santander	GER	9/3/12
91	Lufthansa	US	5/4/12	137	Sharp	US	8/2/12
92	Lufthansa	GER	5/29/12	138	Sharp	GER	8/3/12
93	Max Bahr	GER	11/25/11	139	Sharp	US	9/25/12
94	Mazda	GER	3/15/12	140	Shell	GER	3/4/09
95	Merck	US	3/1/10	141	Shell	GER	10/30/09
96	Merck	US	7/29/11	142	Shell	US	10/30/09
97	Merrill Lynch	US	8/19/11	143	Shell	GER	1/13/11
98	Merrill Lynch	US	9/12/11	144	SolarWorld	GER	9/2/11
99	Merrill Lynch	US	5/1/12	145	SolarWorld	GER	6/1/12
100	Metro	GER	10/6/08	146	Sony	GER	8/24/12
101	Metro	GER	7/17/09	147	Sony	US	8/24/12
102	Metro	GER	6/10/11	148	Sparkasse	GER	7/16/08
103	Morgan Stanley	US	12/15/11	149	Sparkasse	GER	11/12/09
104	Motorola	GER	10/31/08	150	Starbucks	GER	7/3/08
105	Motorola	US	8/13/12	151	TNT	GER	1/29/10
106	Nike	GER	2/12/09	152	TNT	GER	6/28/10
107	Nissan	GER	2/10/09	153	Toshiba	GER	4/17/09
108	Nokia	GER	11/12/08	154	Total	GER	3/10/09
109	Nokia	GER	11/24/11	155	Total	GER	6/19/09
110	Nokia	US	2/8/12	156	Total	GER	3/9/10
111	Olympus	US	6/8/12	157	Toyota	GER	2/13/09
112	Otto	GER	11/18/08	158	Triscuit	US	1/18/12
113	Otto	GER	11/24/11	159	TUIfly	GER	8/19/11
114	Otto	GER	4/20/12	160	UBS	US	8/24/11
115	Panasonic	GER	12/29/08	161	Unicredit	GER	10/19/10
116	Panasonic	GER	5/15/09	162	Unicredit	GER	7/27/11
117	Panasonic	GER	4/28/11	163	Unicredit	GER	10/10/12
118	Panasonic	US	4/28/11	164	United Airlines	GER	6/25/08
119	Panasonic	GER	5/29/12	165	United Airlines	GER	7/24/09
120	Panasonic	GER	11/15/12	166	US Airways	US	10/28/09
121	Pepsi	GER	10/15/08	167	Vattenfall	GER	2/1/12
122	Peugeot	GER	11/21/08	168	vodafone	GER	2/24/09
123	Peugeot	GER	10/27/11	169	vodafone	GER	1/29/10
124	Peugeot	GER	7/13/12	170	vodafone	GER	8/10/12
125	Peugeot	GER	12/12/12	171	Volksbank	GER	4/6/09
126	Philips	GER	11/21/08	172	Volksbank	GER	10/19/12
127	Philips	GER	10/6/09	173	Volvo	GER	6/26/08
128	Philips	GER	10/17/11	174	Whirlpool	US	8/28/09
129	Philips	US	10/17/11	175	Whirlpool	US	10/28/11
130	Philips	GER	9/11/12	176	Yahoo!	GER	10/23/08
131	Philips	US	9/12/12	177	Yahoo!	US	11/10/10
132	Renault	GER	7/25/08	178	Yahoo!	GER	3/7/12
133	RWE	GER	7/18/12	179	Yahoo!	US	4/4/12
134	Santander	GER	10/12/11	176	Yahoo!	GER	10/23/08

Appendix C: Cross-sectional Brand Dispersion Regression Results

TABLE C1
CROSS-SECTIONAL ANALYSIS OF MODERATOR EFFECTS (WLS-REGRESSION)

		Brand rating dispersion		
		Expected sign	Standardized coefficient	(Standard error)
Intercept		+/-	-4.2×10^{-4}	(.018)
Layoff-specific moderators				
Strategic motive	*Proactive (base)*		-	
	Reactive	+/-	-.005	(.012)
Layoff size		+	-.044	(9.6×10^{-7})
Timing of announcement	*After financial crisis*[1]		-	
	During financial crisis[2]	-	.120	(.013)
Country of announcement	*United States (base)*		-	
	Germany	+	-.057	(.013)
Firm-specific moderators				
Prior brand strength		+/-	-.021	(4.4×10^{-4})
Prior brand attention		+/-	.066	(7.7×10^{-4})
Layoff history		+/-	.008	(.007)
Country of origin	*Domestic (base)*			
	Foreign	+/-	-.109	(.013)
R2			*.04*	
F-Statistic			*.77*	
N			*179*	

Notes: Expected returns are based on the market-return model (c); ** p<.05, *** p<.01. Tests are one-sided if clear directional effects are expected, two-sided if not. Standard errors in parentheses. WLS regression, weights: standard deviation of returns in estimation window.
[1)]After financial crisis: 2010-2012; [2)] During financial crisis: 2008-2009.

Appendix D: Robustness Checks of Event Study Application

Appendix D contains several robustness checks with regard to different assumptions regarding estimation and event window, and the calculation of abnormal returns. For the robustness analysis I focus on the market return model. Results with respect to alternative abnormal return models are robust and can be received on request from the author.

Estimation window. Table D1 reestimates the event study specification using an event window with 100 days [-110;-10] for the market return model. Enlarging the event window leads to a reduction of layoff announcements that can be included in the final model (N=170).

Event window. I also tests the robustness of results with respect to possible leakage before the layoff announcement. Table D2 presents the results when applying an event window of 14 days in total [-3;-10] to the market return model.

Event window for moderation analysis. For the moderation analysis of the drivers of CAARs it is necessary to specify end date of the event window. Table D3 and D4 show the results of the cross-sectional analysis with regard to different specifications of the event window [-1;3] and [-1;10].

Table D1

EVENT STUDY RESULTS (MARKET MODEL) – ESTIMATION WINDOW 100 DAYS

Estimation window = 100 days (market return model)												
	Brand attention				Brand strength				Brand rating dispersion			
Day	CAAR [-1,x]	Pos:Neg[1]	Patell-test	BMP-test	CAAR [-1,x]	Pos:Neg[1]	Patell-test	BMP-test	CAAR [-1,x]	Pos:Neg[1]	Patell-test	BMP-test
-1	-.17%	78:92	.59	-1.65 **	-.05%	89:81	-.86	-.66	-.63%	77:93	-.07	-1.03
0	-.16%	75:95*	-1.54 *	-1.19	-.15%	82:88	-.65	-1.96 **	-.59%	75:95*	-.89	-1.10
1	-.14%	79:91	-1.04	-.79	-.29%	75:95*	-1.94 **	-3.32 ***	.04%	90:80	-.72	.05
2	.09%	84:86	-.63	.64	-.42%	74:96**	-3.11 ***	-4.08 ***	-.18%	85:85	.03	.10
3	.28%	85:85	.53	1.48 *	-.47%	70:100**	-3.85 ***	-3.99 ***	-.28%	82:88	.04	-.28
4	.42%	92:78	1.43 *	1.38 *	-.56%	68:102***	-3.75 ***	-3.98 ***	.15%	92:78	-.10	-.11
5	.48%	98:72**	1.77 **	2.28 **	-.54%	64:106***	-3.96 ***	-3.90 ***	.11%	92:78	.13	.57
6	.52%	100:70**	1.91 **	2.40 ***	-.49%	72:98**	-3.55 ***	-3.35 ***	-.27%	78:92	.19	-.51
7	.43%	93:77	1.98 **	2.18 **	-.40%	73:97**	-2.90 ***	-2.57 ***	-.12%	90:80	-.14	.05
8	.26%	94:76*	1.61 *	1.39 *	-.33%	78:92	-2.06 **	-2.09 **	-.31%	77:93	.02	-.57
9	.22%	93:77	.93	1.15	-.36%	72:98**	-1.55 *	-2.30 **	.08%	83:87	-.17	.33
10	.16%	84:86	.93	.87	-.33%	82:88	-1.55 *	-1.90 **	-.25%	86:84	-.17	-.42

Notes: *** p < .01; ** p < .05; * p < .1. Two-sided tests. BMP = Boehmer-Musumeci-Poulsen test. CAAR = Cumulated average abnormal return.

[1)] Significance based on sign test proposed by Cowan (1991).

Table D2
EVENT STUDY RESULTS (MARKET MODEL) – EVENT WINDOW [-3,x]

Estimation window = 60 days (market return model)												
	Brand attention				Brand strength				Brand rating dispersion			
Day	CAAR [-3,x]	Pos:Neg[1]	Patell-test	BMP-test	CAAR [-3,x]	Pos:Neg[1]	Patell-test	BMP-test	CAAR [-3,x]	Pos:Neg[1]	Patell-test	BMP-test
-3	-.01%	88:91	-.21	-.23	.06%	98:81	1.18	1.22	-.58%	91:88	-.76	-.79
-2	.00%	86:93	-.05	-.06	.12%	99:80*	1.52 *	1.57 *	.01%	87:92	.01	.01
-1	-.15%	81:98	-.80	-1.05	.08%	95:84	.83	.80	-.50%	89:90	-.32	-.67
0	-.12%	78:101**	-.48	-.58	-.01%	90:89	-.46	-.42	-.60%	78:101**	-.47	-1.02
1	-.13%	81:98	-.41	-.52	-.14%	84:95	-1.64 *	-1.52 *	.07%	90:89	.13	.35
2	.08%	90:89	.50	.66	-.27%	80:99*	-2.66 ***	-2.46 ***	-.29%	90:89	.00	-.01
3	.24%	87:92	1.10	1.34 *	-.34%	69:110***	-2.86 ***	-2.85 ***	-.34%	85:94	-.06	-.17
4	.36%	95:84	1.40 *	1.74 **	-.42%	69:110***	-3.12 ***	-3.37 ***	.17%	99:80*	.20	.65
5	.44%	101:78**	1.66 **	2.23 **	-.41%	67:112***	-2.83 ***	-3.18 ***	.29%	99:80*	.38	1.34 *
6	.50%	97:82	1.85 **	2.50 ***	-.36%	71:108***	-2.22 **	-2.63 ***	-.23%	83:96	-.02	-.05
7	.41%	97:82	1.48 *	2.19 **	-.28%	77:102**	-1.53 *	-2.00 **	-.05%	91:88	.15	.48
8	.25%	95:84	.89	1.41 *	-.23%	82:97	-1.14	-1.62 *	-.20%	78:101**	-.01	-.04
9	.19%	94:85	.62	1.08	-.25%	79:100*	-1.30 *	-1.90 **	.06%	93:86	.14	.55
10	.11%	87:92	.37	.65	-.23%	88:91	-1.06	-1.48 *	-.19%	90:89	.03	.13

Notes: *** p < .01; ** p < .05; * p < .1. Two-sided tests. BMP = Boehmer-Musumeci-Poulsen test. CAAR = Cumulated average abnormal return.
[1)] Significance based on sign test proposed by Cowan (1991).

Table D3

CROSS-SECTIONAL ANALYSIS OF MODERATOR EFFECTS (WLS-REGRESSION) – EVENT WINDOW [-1,3]

		Brand attention			Brand strength			Brand rating dispersion		
		Exp. sign	Standardized coefficient		Exp. sign	Standardized coefficient		Exp. sign	Standardized coefficient	
Intercept		+/-	.004	(.008)	+/-	.004	(.008)	+/-	-.018	(.017)
Layoff-specific moderators										
Strategic motive	*Proactive (base)*		-			-			-	
	Reactive	+/-	-.118	(.005)	+	.147 **	-.005	+/-	.083	(.012)
Layoff size		-	.170 **	(3.4x10^{-7})	-	-.324 ***	(1.6x10^{-7})	+	-.014	(9.2x10^{-7})
Timing of announcement	*After financial crisis**		-			-			-	
	*During financial crisis**	+/-	.022	(.006)	+	.183 ***	-.003	-	-.087	(.013)
Country of announcement	*United States (base)*		-			-			-	
	Germany	+/-	-.059	(.005)	-	-.146 **	(.003)	+	.132	(.012)
Firm-specific moderators										
Prior brand strength		+	.014	(1.2x10^{-4})	+	.191 ***	(5.9x10^{-5})	+/-	.093	(4.2x10^{-4})
Prior brand attention		+	-.046	(2.5x10^{-4})	+/-	-.208 **	(1.2x10^{-4})	+/-	-.010	(7.4x10^{-4})
Layoff history		+	.085	(.003)	-	-.015	(.001)	+/-	.014	(.007)
Country of origin	*Domestic (base)*									
	Foreign	+	-.010	(.005)	-	-.103	(.003)	+/-	-.069	(.013)
R2			*.05*			*.24*			*.03*	
F-Statistic			*1.15*			*6.58* ***			*.72*	
N			*179*			*179*			*179*	

Notes: ** p<.05, *** p<.01. Two-sided tests. Standard errors in parentheses. WLS regression, weights: standard deviation of returns in estimation window. *After financial crisis: 2010-2012; *During financial crisis: 2008-2009.

Table D4
CROSS-SECTIONAL ANALYSIS OF MODERATOR EFFECTS (WLS-REGRESSION) – EVENT WINDOW [-1,10]

		Brand attention			Brand strength			Brand rating dispersion		
		Exp. sign	Standardized coefficient		Exp. sign	Standardized coefficient		Exp. sign	Standardized coefficient	
Intercept		+/-	-.014 **	(.007)	+/-	.001	(.007)	+/-	-.010	(.017)
Layoff-specific moderators										
Strategic motive	*Proactive (base)*		-			-			-	
	Reactive	+	-.015	(.004)	+	.095	(.004)	+/-	.176 **	(.012)
Layoff size		+	.185 ***	($3.0x10^{-7}$)	-	-.110 *	($2.7x10^{-7}$)	+	-.111	($9.1x10^{-7}$)
Timing of announcement	*After financial crisis**		-			-			-	
	*During financial crisis**	+	.077	(.005)	+	.026 ***	(.005)	-	-.185 **	(.013)
Country of announcement	*United States (base)*		-			-			-	
	Germany	+/-	.112	(.005)	-	-.155 **	(.005)	+	-.049	(.012)
Firm-specific moderators										
Prior brand strength		+	-.037	($1.1x10^{-4}$)	+	-.011	($9.7x10^{-5}$)	+/-	-.049	($4.2x10^{-4}$)
Prior brand attention		+	.124 *	($2.2x10^{-4}$)	+/-	-.006	($2.0x10^{-4}$)	+/-	.134	($7.3x10^{-4}$)
Layoff history		+	.085	(.003)	-	-.049	(.002)	+/-	-.050	(.007)
Country of origin	*Domestic (base)*									
	Foreign	+	-.029	(.005)	-	.031	(.004)	+/-	.003	(.013)
R2			*.07*			*.04*			*.08*	
F-Statistic			*1.49*			*.96*			*1.78 **	
N			*179*			*179*			*179*	

Notes: ** p<.05, *** p<.01. Two-sided tests. Standard errors in parentheses. WLS regression, weights: standard deviation of returns in estimation window. *After financial crisis: 2010-2012; *During financial crisis: 2008-2009.

PAPER III: HOW DO BRANDS GENERATE VALUE FOR INVESTORS? IT's FROM NEW BUSINESS AND COMPETITIVE DISTINCTIVENESS

Authors: Marc Fischer, Max Backhaus, Tobias Hornig

Abstract

Prior research has shown that brands contribute to firm value. Investors assess the value of a firm by forming expectations about four main drivers: profitability, earnings growth, capital cost, and the persistence of excess return. There is, however, little knowledge about how exactly brands generate value for investors, i.e. which value drivers they influence.

Based on a broad sample of firms across a variety of industries, the authors measure the impact of costumer-based brand equity on the four value drivers and ultimately firm value. The analysis produces interesting insights into the sources of value creation from brands. It turns out that brands primarily impact investors' expectations about future earnings growth and the persistence of excess returns. The impact on expected profitability, however, is surprisingly small; and there is no uniform effect on the cost of capital. Hence, brands generate value for investors by their power to expand the business and to establish competitive distinctiveness.

Keywords: Brand equity, advertising, corporate valuation, marketing strategy, econometric models

1 Introduction

According to the theory of efficient capital markets, all available information about a company is incorporated into its stock price (Fama 1970). The stock price rises if unexpected new information arrives that lead investors to increase expectations regarding future cash flows. What happens if investors learn about an increase in brand strength? Extant prior research (e.g., Mizik and Jacobson 2008; Srinivasan and Hanssens 2009) shows that this is likely to result in a higher firm value. However, we do not know which expectations exactly investors update when they incorporate new information about brand performance and how that translates into higher firm value. Moreover, the magnitude of the impact is not well under-stood and only few marketers might have an intuition for that.

Marketing practitioners typically think about how marketing actions change intermediate out-comes such as awareness that drive product-market results, e.g., market share, be it with a time lag. They are also increasingly aware of the power of marketing to create market-based assets such as brand equity that reflect the potential for future cash flow generation in a condensed form (e.g., Srivastava et al. 1998). Marketing managers' mental model is predominantly a demand model. In contrast, investors often have a different model in mind. Their model derives from corporate valuation. Instead of market share and demand responsiveness they focus on the spread between the return on invested capital and capital cost (excess return), future earnings growth, the cost of capital, and the persistence of excess returns. Of course, both models have multiple connections. A larger return on invested capital, for example, may arise from a higher willingness-to-pay (Keller 1993). But the connections between marketing investment and these value drivers are not well documented and quantified, yet.

In this work, we attempt to quantify these connections. For this purpose, we adopt the established discounted cash flow approach to decompose firm value into the value of current earnings strength and the value of investments into future growth. Mizik (2014) has shown that 90 percent of the total financial impact of brand equity is realized in the future and only 10 percent through current earnings. According to financial theory (e.g., Copeland et al. 2013), the value of future growth is mainly driven by four factors: the return on invested capital (ROIC), the cost of capital (WACC), the earnings growth rate (EGR), and the time period until the advantage in superior returns has eroded by competition (S - sustainability of excess return). We investigate how changes in advertising expenditures and customer-based brand equity (CBBE) impact these drivers of firm value. Specifically, we ask the following research questions:

- How large is the relative impact (measured as elasticity) of CBBE on each of the four value drivers and its mediated impact on firm value?
- Which is the most influential route of value generation for brands, i.e. via improving which value driver?
- Does the relative impact of CBBE on firm value and value drivers vary across firms and industries?
- How do advertising expenditures impact (measured as elasticity) CBBE, then its value drivers, and ultimately firm value?
- Do advertising investments in CBBE pay off in firm value?

We answer these questions by analyzing a broad sample of 614 firms and more than 1,200 brands covering a period of 9 years from 2005 to 2013 across a wide range of industries. Our database includes retailers, durable and non-durable products, as well as services. Though a healthy body of research on the role of brands for value generation exists, we cannot use it to answer our questions for two main reasons. First, we are not aware of a study that quantifies the impact of brands on the sustainability of excess re-turns, which is a key value driver. Second, we need to estimate the impact of CBBE on value drivers and firm value for each individual firm before we can aggregate them to generalizable results. This is necessary to avoid the aggregation bias from using aggregate market-level information to compute our non-linear effect measures (Christen et al. 1997). Parameter estimates and key (financial) variables, however, are typically not available at the firm level from prior studies.

The substantive insights into the magnitude of the effects of advertising and CBBE on value drivers and ultimately firm value are our main contribution. We also contribute to the literature by introducing and studying the sustainability of excess returns, which quantifies the important but unobservable construct of competitive advantage in financial terms. The magnitudes of our focal effects are not easy to predict, neither from theory nor prior empirical research. It turns out that brands primarily impact investors' expectations about future earnings growth and the persistence of excess returns. The impact on expected profitability, however, is surprisingly small; and there is no uniform effect on the cost of capital. Hence, brands generate value for investors by their power to expand the business and to establish competitive distinctiveness.

The remainder of the paper is structured as follows: In the next section we summarize the empirical literature on value drivers and the value relevance of brand equity. We then develop our modeling framework to decompose firm value and specify the estimation equations. The following section informs about the data sample and estimation issues. It is followed by a discussion of results. We conclude the paper with implications for further research.

2 Background

2.1 Corporate Valuation

Many approaches to the valuation of companies exist. It is beyond our scope to review the corporate valuation literature in detail (see, for example, Koller et al. 2015; Damodaran 2012). According to Damodaran (2012), valuation approaches can be broadly categorized into two classes of direct and relative valuation. Relative valuation refers to the multiplier analysis where a set of similar companies is identified and their market value is linked to a common performance metric such as sales or earnings (EBIT). While widely used in practice, a challenge is to find the set of firms that is comparable to the focal firm. Another limitation to this approach is that the sources of value generation are not apparent.

Direct valuation follows the framework of discounted cash flow analysis (DCF). Here, the idea is to estimate the intrinsic value of a company based on its fundamentals. It involves a projection of future cash flows that are discounted at an appropriate rate that reflects the riskiness and the capital structure of the firm. DCF valuation is attractive from both a theoretical and practical point of view. It requires being explicit about the input information for cash flow projections and coincides with the market value of a firm, at least in theory. Moreover, it allows identifying major drivers of value generation, which are (e.g., Copeland et al. 2013; Koller et al. 2015): the return on invested capital (ROIC), the cost of capital (WACC), the earnings growth rate (EGR), and the sustainability of excess return (ROIC-WACC > 0). Our interest centers on these four value drivers.

2.2 **Literature on Brand Assets**

Srivastava et al. (1998) introduced the concept of market-based assets and their contribution to the creation of firm value. A large body of research has developed since then. Since our focus is on brands we review the stream of related brand studies. This literature can be summarized into two groups. The first group of studies (e.g., Barth et al. 1998; Mizik and Jacobson 2008) attempts to establish evidence that brands are indeed valuable intangible assets, which contribute to shareholder/firm value. Without doubt, there is overwhelming support for the value relevance of brands, which is emphasized by Edeling and Fischer (2016). Their meta-analysis also reveals moderators of brand-related firm value effects, e.g., the state of the economy and competitive intensity. However, the aggregation level of the meta-analysis is too high to provide insights into the mediating role of value drivers such as the sustainability of excess return. In addition, Edeling and Fischer (2016) call for more research at the firm level that helps understand the heterogeneity in firm value effects between industries and firms. We follow this call and extend the literature in this direction.

Table 1 summarizes relevant studies of the second group, which investigate the role of brands for individual components and drivers of firm value. As is evident from the table, the majority of these studies (5 out of 10) focus on the relation between brands and risk factors. While strong brands appear to reduce the cost of debt, the findings on equity cost, i.e. systematic risk, are mixed. Bharadwaj et al. (2011) find a positive relation, but Rego et al. (2009) report a negative relation. Two other studies do not show any significant relationship. Quite in contrast, the findings on profitability are consistent and suggest that strong brands improve profitability.

Katsikeas et al. (2016) conclude that research on the impact of brands on profit/earnings growth is surprisingly thin. Indeed, we were able to find only one study (Morgan et al. 2009) that directly investigates the relationship between brand management capability and profit growth. This study finds no significant impact of brands on profit growth, which is against our intuition. However, we note that the focal variable is how managers evaluate their own brand *management capabilities*, which is not the same as the brand outcome perceived by customers. We acknowledge that growth information is implicitly contained in a sales or earnings response model. However, such a model does not capture the important quality of brands to create growth from entering new markets (e.g., new categories, new countries). This limitation also applies to the CLV modeling frameworks of Rust et al. (2004) and Stahl et al. (2012), which explicitly model growth through acquiring new customers but within the boundaries of a given market. We were not able to locate a study on the impact of brands on the sustainability of excess returns.

Table 1: Empirical Research on the Value Relevance of Brands

Reference	Data	Brand Metric	Model	Dependent variables	Key independent variables	Key brand-related findings	Elasticity obtainable?	Industry-level effects?
Aaker & Jacobson (2001)	Financial data (1988-1994)	CBBE (customer survey)	Linear regression	Stkr, ROE	CBBE, ROE	CBBE impacts ROE and Stkr positively	Yes	No
Bharadwaj, *et al.* (2011)	Financial data (2000-2005)	CBBE (customer survey)	Linear regression	Stkr, Beta, idiosyncratic risk	CBBE, earnings	CBBE impacts Sktr and Beta positively, idiosyncratic risk negatively	No	No
Fischer & Himme (2017)	Financial data (2005-2012)	CBBE (customer survey)	Dynamic, simultaneous equation system	Financial resources, credit spread, financial leverage	ADV, CBBE	ADV impacts CBEE positively, CBBE impacts credit spread and leverage negatively and financial resources positively	Yes	No
Himme & Fischer (2014)	Financial data (1989-2006)	FBE (Interbrand)	Linear regression	Beta, credit spread	FBE, customer satisfaction, reputation	FBE impacts spread negatively, no impact on Beta and WACC	No	No
Luo et al. (2012)	Financial data (2008-2011)	CBBE (customer survey)	VAR model	Stkr, idiosyncratic risk, trading volume, CBBE, CBBE dispersion	Stkr, idiosyncratic risk, trading volume, CBBE, CBBE dispersion	CBBE impacts Stkr positively, CBBE dispersion impacts Sktr and risk negatively	Yes	No
Mizik (2014)	Financial data (2000-2010)	CBBE (customer survey)	Linear regression	Stkr, ROA	CBBE, ROA	CBBE impacts Stkr and ROA positively	No[1)]	No
Morgan, *et al.* (2009)	Manager survey, financial data (cross-section)	Brand management capability (manager survey)	Linear regression	Revenue growth, margin growth, profit growth	Capabilities of brand management, market sensing, CRM	No impact of brand mgmt. capabilities on profit growth, positive impact on revenue growth, negative impact on margin growth	Yes	No
Rego, *et al.* (2009)	Financial data (2000-2006)	CBBE (customer survey)	Linear regression, ordered logit model	Credit rating, systematic and nonsystematic risk	CBBE, ROA	CBBE impacts credit ratings positively and systematic and nonsystematic risk negatively	Partially	No
Rust, *et al.* (2004)	Consumer survey (cross-section)	CBBE (customer survey)	Choice model	Brand choice, customer equity	Brand-related, volume-related, relationship-related drivers	Brand-related drivers impact brand choice and customer equity positively	No	No
Stahl, *et al.* (2012)	Company and customer data (1998-2008)	CBBE (customer survey)	(Aggregate) choice model, linear regression	CBBE, acquisition rate, retention rate, profit margin, CLV	ADV, CBBE, marketing mix	ADV impacts CBBE positively, CBBE impacts profit margin and CLV positively	Partially[1)]	No
This study	Financial data (2005-2013)	CBBE (customer survey)	Linear regression, hazard model	CBBE, ROIC, EGR, WACC, S, FV	ADV, CBEE, ROIC, WACC, S	ADV with positive impact on CBBE, CBBE positively impacts ROIC, EGR, S, FV; No effect on WACC	Yes	Yes

Notes: ADV = advertising, CBBE = customer-based brand equity, FBE = financial brand equity, Stkr = stock return, ROA = return on assets, ROE = return on equity, CRM = customer relationship management, WACC = weighted average cost of capital, ROIC = return on invested capital, EGR = earnings growth, S = sustainability of excess returns, FV = firm value. [1)] Elasticities cannot be obtained from z-standardized variables

Collectively, prior research on the role of brands for the four value drivers provides important insights (see Table 1 again). However, its does not allow answering our research questions. First, the literature does not sufficiently cover all four drivers. Second, to be able to compare the role of drivers and calculate their ultimate firm value effects we need effect-size estimates in elasticity format. This information is not always obtainable. Third, if we want to derive firm value effects of brands via the four value drivers on an aggregate, generalizable basis, we need to estimate them at the firm level. Using aggregate information in a non-linear valuation model produces biased results (Christen et al. 1997). Fourth, firm-level results and industry-specific estimates are usually not available from prior studies.

3 Theoretical Framework and Hypotheses

We adopt a DCF framework to derive firm value. Generally, valuators follow two approaches, often in combination, a formula approach and a spreadsheet approach (Copeland et al. 2013). The spreadsheet approach requires estimating free cash flows explicitly for each single period of a forecast interval. It usually involves the collection of many detailed financial information about the company. The formula approach provides a closed-form solution to the valuation task. The big advantage of this approach is that it is compact and requires only forecasts of the key value drivers. This simplicity comes at the cost of a lower precision of forecasts for earnings. Because explicit earnings forecast are also subject to error, which increases in time, both approaches lead to very similar value estimates, especially if the time horizon is long.

For our purpose to produce generalizable results for a large sample of firms, the formula approach appears to be the most appropriate. As we show later, it also enables us to estimate the sustainability of excess returns from observed market values of companies.

3.1 A Formula Approach to Corporate Valuation

In a discounted cash flow framework, a firm's value equals the present value of the expected future cash flows. When valuing a business, these expected cash flows are usually generated from estimated earnings in future periods, which in turn are determined by current earnings and the expected growth rate in these earnings (Koller et al. 2015). Thus, firm value in period $t = 0$, FV_0, is equal to the sum of discounted future cash flows:

$$FV_0 = \frac{EBIT_1 \times (1-\tau) - I_1}{(1+WACC)} + \frac{EBIT_2 \times (1-\tau) - I_2}{(1+WACC)^2} + \frac{EBIT_3 \times (1-\tau) - I_3}{(1+WACC)^3} + \ldots,$$

(1)

where $EBIT_t$ denotes earnings before interest and tax in period t, I_t are investments in new capital in period t, $WACC$ is the weighted average of cost of capital, and τ denotes the cash tax rate. Note that $WACC$ and τ do not have a time subscript, i.e. they are constant. This assumption is not too restrictive and frequently applied in practice (including spreadsheet valuations) because these metrics only change due to important exogenous shocks, e.g., a recession or a change in tax law, which are hard to predict.

Copeland et al. (2013, 497ff) show that Equation 1 can be simplified and rearranged in a way that it decomposes firm value into two parts (see the Appendix C):

$$FV_0 = \underbrace{\frac{EBIT_1 \times (1-\tau)}{WACC}}_{\substack{\text{Value of current} \\ \text{earnings strength}}} \times \underbrace{\left[1 + \frac{(ROIC - WACC) \times EGR \times S}{ROIC \times (1+WACC)}\right]}_{\text{Value of growth expectations}} \quad (2)$$

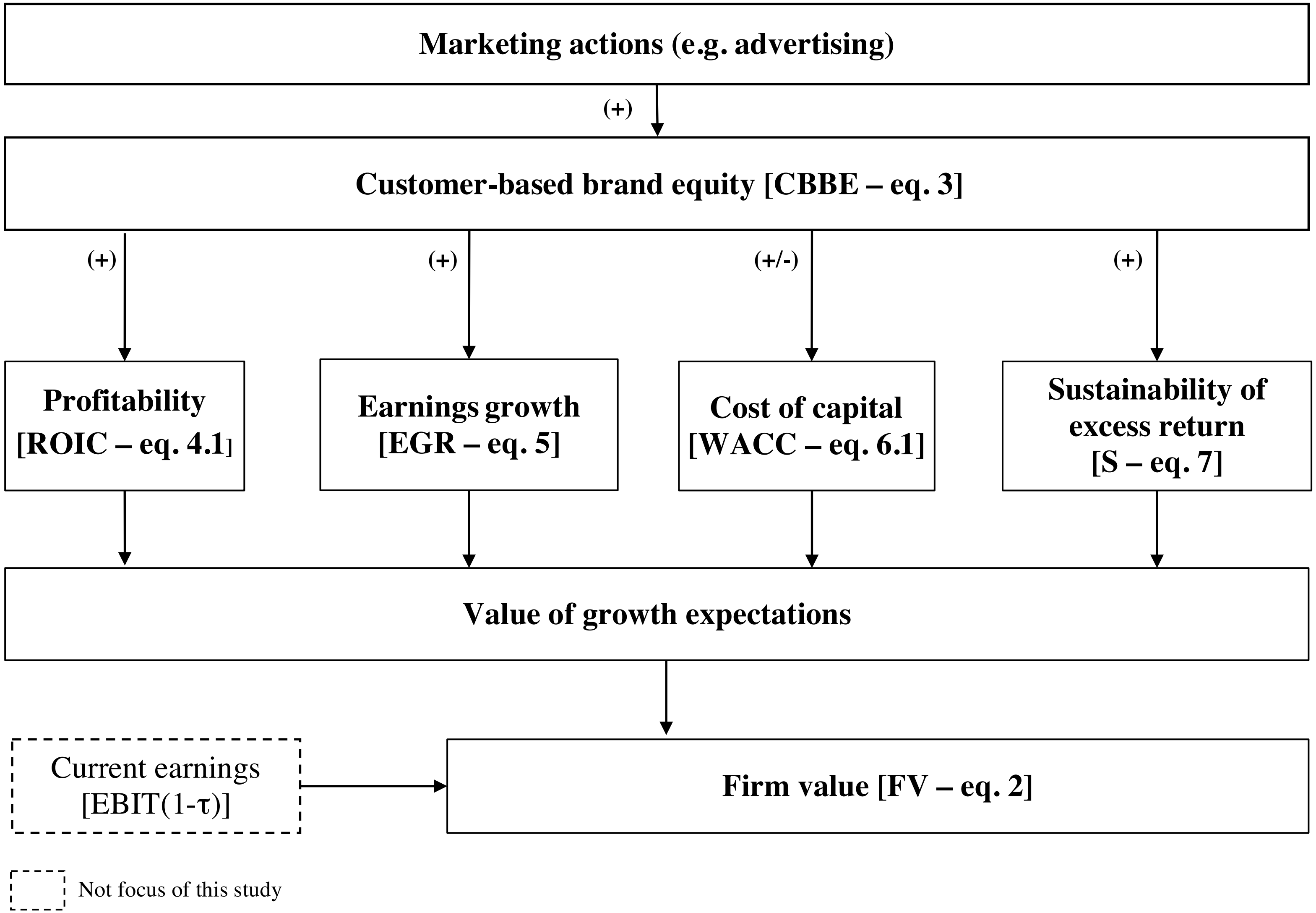
The first part of Equation 2 collects future cash flows that are generated from the capital invested at the time of valuation. It reflects the value of the current earnings strength. The second summand reflects the value of growth expectations. *ROIC* measures the average rate of return on new investments that the firm expects to generate from its future projects. *EGR* represents the forecasted average rate by which earnings grow. Note that this growth is only value generating as long as the rate of return exceeds the cost of capital. A fundamental assumption of our valuation model is that these excess returns cannot be maintained forever. This assumption seems reasonable as no competitor can expand and earn more than the cost of capital on the investment in a long-run competitive equilibrium (Demsetz 1982). Only firms with a significant competitive advantage can sustain excess return over a longer time (Dierickx and Cool 1989). We call the length of this period the *sustainability* of *excess return* and denote it with *S*.

3.2 **Theoretical Framework of Value Drivers**

Equation 2 is our core valuation equation. Our interest centers on explaining the relative impact brand building has on the value drivers *ROIC*, *EGR*, *WACC*, and *S*. Figure 1 summarizes the theoretical framework that guides our empirical analysis. Consistent with prior research (e.g., Stahl et al. 2012), we propose that marketing actions such as advertising investments contribute to brand building, which we measure in terms of customer-based brand equity (CBBE). We assume that an important portion of firm value comes from its growth expectations (Ghesquieres et al. 2016). We propose that CBBE potentially impacts the value of these growth expectations via its value drivers.

Based on our valuation model, we set up a system of equations that can be estimated with econometric methods. Specifically, we specify five equations that help quantify and compare the different routes of value generation that arise from advertising and other investments into brands. Figure 1 shows our focal endogenous variables and the associated estimation equation. Before we turn to the econometric specifications we briefly discuss our rationale for the impact of CBBE on the four value drivers in form of testable hypotheses.

Figure 1: Theoretical Framework of Value Drivers



3.3 **Hypotheses**

Srivastava et al. (1998) suggest various market performance effects that result from market-based assets, which then translate into shareholder value because they may accelerate and enhance cash flows and reduce the volatility and vulnerability of cash flows. From this framework and extant brand literature, we derive arguments for the differential effects of CBBE on the four value drivers.

Strong and differentiated brands enjoy monopolistic power that enables them to command a price premium (e.g., Ailawadi et al. 2003). For example, the Porsche Cayenne and the VW Touareg result from a joint development initiative and are built on the same platform. Manufacturing costs are comparable, but Porsche is able to ask for a higher price because of the strength of its brand. Following Keller (1993), high CBBE is also associated with a customer base that is more responsive to marketing activities such as advertising and promotion. As a result, the marginal cost of marketing and sales are lower. These two effects directly improve the profit margin and lead us to our first hypothesis:

H1: Higher CBBE is associated with higher return on invested capital (ROIC).

It has long been argued that strong brands offer a higher potential to extend existing product lines, expand into related and new product categories, enter international markets, and increase revenues by licensing brand names to be used in other categories (e.g., Lane and Jacobson 1995; Srivastava et al. 1998). Luxury fashion brands such as Hugo Boss demonstrate how the brand name helped expand the business into new categories (e.g., women's wear), open new stores across the world, and license the brand for sunglasses, cosmetics, etc. As a result, revenues and share price of the company rose considerably over the last 20 years. It is the greater awareness and positive associations potential customers hold with respect to a strong brand that reduce entry barriers and result into faster trial, referrals, and adoption and stronger preferences for the new product (Keller 1993). These effects in turn lead to higher and faster earnings for the brand. Thus,

H2: Higher CBBE is associated with higher earnings growth (EGR).

The effect of CBBE on WACC is more complex and less obvious. To better understand the effect it is helpful to decompose WACC into its components. WACC is a capital-structure weighted average of the cost of equity and debt. Brands supposedly have an impact on the risk components of debt and equity cost and the capital structure (e.g., Fischer and Himme 2017; Rego et al. 2009).

Strong brands signal excellent marketing capabilities that ensure high inflow of cash in the future. This is an important criterion in the rating process of credit-rating agencies such as Standard & Poor's because it strengthens the firm's capability to fulfill its liabilities. Hence, CBBE should improve the rating, i.e. lower debt cost (Himme and Fischer 2014; Rego et al. 2009).

It has also been argued that CBBE lowers the systematic risk or equity risk, respectively (Rego et al. 2009). This is because strong brands tend to have more loyal customers, higher awareness rates and stronger preferences. In an economic downturn, these factors prevent customers from switching to other brands and retailers from delisting the brand reducing the volatility of cash flows. On the other hand, Himme and Fischer (2014) and others argue that CBBE may also increase systematic risk, in particular in times of economic prosperity. Strong brands respond to an upswing with faster growth (see H2). This growth comes with a side effect of higher cash flow volatility that increases the systematic risk.

Finally, Fischer and Himme (2017) suggest that stronger brands are associated with lower leverage ratios. Because tangible assets (e.g., property, plant, and equipment) serve as collateral, finance theory suggests that firms with a higher ratio of tangible over intangible assets (such as brands) issue more debt (Titman and Wessels 1988). In addition, strong brands help firms attracting equity capital because investors expect higher stock returns (Mizik and Jacobson 2008). Finance management prefers equity over debt capital because it provides them with more flexibility, especially in situations of financial distress. All these arguments suggest that firms with stronger brands have a lower debt-to-equity ratio, which in turn increases WACC.

In view of these opposing influences of CBBE on WACC, we do not propose a unidirectional relationship. We rather expect that the relation is insignificant or marginally significant at best across firms. It seems to be more likely that some firms face a negative total effect of CBBE on their WACC and others a positive one, depending on market situation and firm characteristics.

Excess returns can only be realized if the firm is able to maintain a competitive advantage. The resource-based view of the firm posits that a firm reaches a sustainable competitive advantage by virtue of unique resources that are rare, valuable, inimitable, and non-substitutable, as well as firm-specific (e.g., Makadok 2001). The brand is such a strategic market-based asset that protects the company from competition and makes its future cash flows less vulnerable (Srivastava, Shervani, and Fahey 1998). Consumers have higher preferences for strong brands. These preferences impose switching costs that result into greater loyalty (Chaudhuri and Holbrook 2001). The unique position also shields the brand against competitive actions along the marketing mix (Mela et al. 1997). Eventually, strong brands increase barriers for entry of new competitors (Erickson and Jacobson 1992). Hence,

H3: Higher CBBE is associated with a longer period of excess returns (S).

4 Econometric Model Specifications

4.1 Modeling Requirements

Our empirical model includes five key constructs, CBBE and the four value drivers, which we assume to be endogenous. We start specifying the CBBE equation followed by the equations for profitability, earnings growth, capital cost, and sustainability of excess return. Before we turn to the exact specifications, we briefly discuss several requirements our equations have to satisfy. Specifically, we need to model expectations and account for dynamics, heterogeneity, diminishing returns, and the influence of control variables.

Expectations. Market valuation of a business is based on investors' expectations about the stream of future cash flows. Thus, our focal value driver variables are *expectations* about ROIC, earnings growth, WACC, and sustainability of excess return. Ideally, we may ask investors for their expectations. For earnings growth, we have such information from a regular survey among analysts available. We derive the expected sustainability of excess return from firm market values. We adopt a modeling approach to measure expectations for ROIC and WACC.

Heterogeneity. We pool data from various firms and markets for model estimation. We thus need to control for idiosyncratic differences in our focal constructs that arise from firm and market differences. We include firm size and market concentration as two observable heterogeneity variables. In addition, we specify the intercept in each equation as firm-specific and assume that these effects follow a random distribution (e.g., Himme and Fischer 2014). By incorporating firm-specific effects, we also effectively control for omitted firm characteristics such as management luck or other market-based assets, which we do not observe. Since we model the unobserved firm characteristics in a Bayesian fashion as part of the intercept they do not appear in the error term. We thus circumvent endogeneity issues that may arise when other predictors correlate with unobserved firm characteristics as part of the error term. Finally, we specify the parameters for advertising in the brand equity equation and CBBE in all other equations to be heterogeneous. This enables us to measure firm differences in their effectiveness of influencing CBBE, the value drivers, and ultimately firm value.

Dynamics. We include the lagged dependent variable to control for carryover effects. This specification corresponds to the established and parsimonious notion of geometrically distributed lags (Hanssens et al. 2001). Another advantage is that the impact of other predictors can be interpreted more readily as (Granger) causal. It also controls for different initial conditions (Tuli and Bharadwaj 2009). We check for other dynamics such as non-stationary time-series and serially correlated error terms but do not find evidence for these characteristics.[16]

Diminishing Returns. Marketing investments should be subject to diminishing returns, which is also a necessary condition for the existence of an optimal investment level (Hanssens et al. 2001). We take the log of advertising and other expenditure variables in the brand equity equation, which can be interpreted as our marketing productivity equation.

Control variables. We include various control variables that are assumed to impact our focal constructs. These controls cover strategic variables (e.g., R&D expenditures), financial variables (e.g., financial leverage), and variables of operational efficiency (e.g., operating margin). Prior research in finance, accounting, marketing, and strategy guides the selection of these variables. We also account for economy-wide, period-specific influences by incorporating the growth in U.S. GDP. Since our focus is on the effects of CBBE on the value drivers, we do not discuss the control variables in detail. Appendix F lists the various control variables, assigns the equation where they appear, and provides reference from supporting literature.

[16] The test for common factors (Greene 2012) does not suggest serially correlated errors ($p > .10$). Using panel unit-root tests (Fisher-type based on augmented Dickey-Fuller tests; Choi 2001), we cannot reject the null hypothesis of non-stationary time-series.

4.2 Specification of Estimation Equations

CBBE Equation. For measuring the impact of advertising investments and other variables on CBBE, we specify the following equation

$$\begin{aligned} CBBE_{it} &= a_{0i} + a_1 CBBE_{it-1} + a_{2i} \ln ADV_{it-1} + a_3 \ln RD_{it-1} + a_4 \ln OE_{it-1} \\ &\quad + a_5 OPM_{it-1} + a_6 EARN_{it-1} + a_7 SIZE_{it-1} + a_8 CONC_{it-1} + u_{1it}, \end{aligned} \tag{3}$$

with $u_{1it} \sim N\left(0, \sigma_{u1}^2\right)$, $\mathbf{a}_i = \bar{\mathbf{a}} + \Psi_a \mathbf{w}_{ai}$, and $Var\left(\mathbf{a}_i\right) = \Psi_a \Psi_a'$,

where **a** denotes the vector of parameters to be estimated, i is an index for firm, t is an index for period, and u is an i.i.d. error term. Appendix Table A1 summarizes the symbols and abbreviations we use for predictor variables in Equation 3 and the following equations. Vector $\mathbf{a}_i$ includes the parameters that are assumed to be firm specific, where $\bar{\mathbf{a}}$ is the mean and $\mathbf{w}_{ai}$ is a random vector with mean zero and variance matrix equal to an identity matrix. We allow the firm-specific parameters a_{0i} and a_{2i} to be correlated. The matrix psi provides the correlation and variances in the distribution of $\mathbf{a}_i$. We impose the same flexible structure on the parameter vectors in all other equations.

To account for diminishing returns in expenditure variables, such as advertising, we take the log of these variables. We measure carryover by the parameter a_1. The use of lagged values for the predictor variables avoids potential endogeneity issues. Consistent with the next equation for ROIC, we can also interpret Equation 3 as a model for expectations on CBBE.

Profitability Equation. Let $\widetilde{ROIC}_{it}$ measure the expected return on invested capital. We assume that investors form their expectations on the basis of the following information set

$$\begin{aligned} \widetilde{ROIC}_{it} &= b_{0i} + b_1 ROIC_{t-1} + b_{2i} CBBE_{it-1} + b_3 ADV_{it-1} + b_4 RD_{it-1} \\ &\quad + b_5 OE_{it-1} + b_6 LEV_{it-1} + b_7 GDPGR_{t-1} + b_8 SIZE_{it-1} + b_9 CONC_{it-1} + u_{2it}, \end{aligned} \tag{4.1}$$

with $u_{2it} \sim N\left(0, \sigma_{u2}^2\right)$, $\mathbf{b}_i = \bar{\mathbf{b}} + \Psi_b \mathbf{w}_{bi}$, and $Var\left(\mathbf{b}_i\right) = \Psi_b \Psi_b'$, where **b** denotes the parameter vector to be estimated and all other terms are as defined before. Note that investors can only use past information to build expectations about future ROIC. In period t, expected $\widetilde{ROIC}_{it}$ then explains realized $ROIC_{it}$ up to an error, which we denote with φ and assume to be i.i.d. normal distributed. Thus

$$ROIC_{it} = \widetilde{ROIC}_{it} + \varphi_{it}, \text{ with } Cov\left(u_{2it}, \varphi_{it}\right) = 0 . \tag{4.2}$$

Inserting Equation 4.1 into 4.2 then produces our estimation equation that includes only observable quantities and that we take to the data.

Earnings-Growth Equation. We specify expected earnings growth as follows

$$\begin{aligned}\widetilde{EGR}_{it} = {} & c_{0i} + c_1\widetilde{EGR}_{t-1} + c_{2i}CBBE_{it-1} + c_3ADV_{it-1} + c_4RD_{it-1} + c_5OE_{it-1} \\ & + c_6EARN_{it-1} + c_7D\_NEARN_{it-1} + c_8LEV_{it-1} + c_9ROIC_{it-1} \\ & + c_{10}IR_{it-1} + c_{11}GDPGR_{t-1} + c_{12}SIZE_{it-1} + c_{13}CONC_{it-1} + u_{3it},\end{aligned} \tag{5}$$

$$\text{with } u_{3it} \sim N\left(0, \sigma^2_{i,u3}\right), \ \mathbf{c}_i = \overline{\mathbf{c}} + \boldsymbol{\Psi}_c\mathbf{w}_{ci}, \text{ and } Var\left(\mathbf{c}_i\right) = \boldsymbol{\Psi}_c\boldsymbol{\Psi}'_c,$$

where **c** denotes the parameter vector to be estimated and all other terms are as defined before. Earnings growth expectations are available to us from a regular survey among analysts. Since the mean is subject to sampling error that depends on the number of analysts, it introduces heteroskedasticity into the error variance. We account for this by using the number of analysts as a weight when estimating the model.

Cost-of-Capital Equation. Building on previous research in the marketing-finance interface (e.g., Rego et al. 2009, Himme and Fischer 2014), we specify the following equation to predict expected cost of capital

$$\begin{aligned}\widetilde{WACC}_{it} = {} & d_{0i} + d_1WACC_{t-1} + d_{2i}CBBE_{it-1} + d_3OPM_{it-1} + d_4LEV_{it-1} + d_5INT_{it-1} + d_6DIV_{it-1} \\ & + d_7A\_GROWTH_{it-1} + d_8LIQ_{it-1} + d_9SIZE_{it-1} + d_{10}CONC_{it-1} + u_{4it},\end{aligned} \tag{6.1}$$

$$\text{with } u_{4it} \sim N\left(0, \sigma^2_{u4}\right), \ \mathbf{d}_i = \overline{\mathbf{d}} + \boldsymbol{\Psi}_d\mathbf{w}_{di}, \text{ and } Var\left(\mathbf{d}_i\right) = \boldsymbol{\Psi}_d\boldsymbol{\Psi}'_d,$$

where **d** denotes the parameter vector to be estimated and all other terms are as defined before. Expected $\widetilde{WACC}_{it}$ explains realized $WACC_{it}$ in t up to an error, which we denote with η and assume to be i.i.d. normal distributed. Thus

$$WACC_{it} = \widetilde{WACC}_{it} + \eta_{it}, \text{ with } Cov\left(u_{4it}, \eta_{it}\right) = 0. \tag{6.2}$$

Inserting Equation 6.1 into 6.2 then produces our estimation equation.

Sustainability-of-Excess-Return Equation. We now turn to our last estimation equation to explain expected sustainability of excess returns. Recall that this variable measures the length of the period during which the firm is expected to earn rents above its cost of capital. As a result, $\tilde{S}$ is a duration variable that is nonnegative by definition. This requires an appropriate distributional assumption and estimation approach, such as a hazard model (Greene 2012). Several distributions have been suggested for duration variables including Weibull, Gamma, and Lognormal distributions. The Weibull distribution is a very flexible distribution that allows for both monotonic and non-monotonic shapes of the marginal distribution and encompasses the exponential distribution as a special case (Greene 2012). We adopt this distribution but also test whether this assumption is supported by our data (see the Appendix Figure H1).

Note since the duration of superior rents is a unique event that follows a random distribution, it is conceptually not apt to include the lagged dependent variable into the model. We specify our last equation for expected sustainability of excess returns as follows

$$f\left(\tilde{S}_{it}\right) = \left(\lambda_{it} p\right)\left(\lambda_{it}\tilde{S}\right)^{p-1} e^{-\left(\lambda_{it}\tilde{S}\right)^{p}}, \text{ for } \tilde{S}_{it} > 0,\ \lambda > 0,\ p > 0,$$
$$\text{with } \lambda_{it} = \exp\left[-\begin{pmatrix} g_{0i} + g_{1i}CBBE_{it-1} + g_2 ADV_{it-1} + g_3 RD_{it-1} + g_4 OE_{it-1} \\ +g_5 A\_GROWTH_{it-1} + g_6 GDPGR_{t-1} + g_7 SIZE_{it-1} + g_8 CONC_{it-1} \end{pmatrix}\right], \tag{7}$$

with $\mathbf{g}_i = \overline{\mathbf{g}} + \mathbf{\Psi}_g \mathbf{w}_{gi}$, and $Var\left(\mathbf{g}_\mathbf{i}\right) = \mathbf{\Psi}_g \mathbf{\Psi}'_g$, where $f\left(\tilde{S}\right)$ describes the density of expected sustainability $\tilde{S}$, λ is the location parameter and p is the scale parameter that characterize the moments of the distribution and are to be estimated, **g** denotes the parameter vector to be estimated, and all other terms are as defined before. Again, we consider one-period lagged values for all predictor variables to account for the fact that investors use prior information levels when forming their expectations. We adopt a hazard function approach to estimate the parameters in Equation 7 (Greene 2012).

5 Data and Estimation

5.1 Data Sources

We collected data on an annual basis from various databases. These databases include Harris Poll EquiTrend, COMPUSTAT, Bloomberg's, the Center for Research in Security Prices (CRSP), and I/B/E/S. Our data collection covers the years from 2005 to 2013. The sample includes 614 companies from major industry sectors, such as financial institutions, consumer packaged goods, etc. The total number of observations exceeds 5,000. But, because we do not necessarily observe all variables for each firm and period the effective sample size is considerably smaller and varies by equation.

Measures. We use the established EquiTrend data to measure CBBE (e.g., Bharadwaj, Tuli, and Bonfrer 2011). The measure is a latent variable scaled to a 0-100 index and estimated by using four individual-level consumer variables: familiarity, perceived quality, purchase consideration, and distinctiveness (see Appendix E for a detailed description). Following prior practice (Rego et al. 2009), we aggregate mean ratings of different brands for multi-brand firms.

We use COMPUSTAT data to construct our ROIC variable. Specifically, we use operating cash flow (DATA 308), which is defined as net operating profit after tax, and invested capital (DATA 37) to calculate the financial ratio.

Our expected earnings growth variable represents the 5-year consensus forecast of analysts that is provided by the I/B/E/S database. These analyst forecasts are broadly considered by investors (Kothari 2001).

Bloomberg provides all information we need to calculate WACC. We follow the standard approach (e.g., Rego et al. 2009) and estimate firm-specific beta on a yearly basis by using daily stock returns for each firm. Together with information on credit spreads, the yield of a risk-free bond, and the capital structure, we obtain WACC for each year and firm.

Sustainability of excess return is a latent construct and not observable. From our DCF model, however, we know that it is an inherent part of the valuation process. Assuming efficient capital markets, it is implicitly incorporated in a firm's current market value since market capitalization provides an unbiased estimate of the value of the firm. Consequently, we solve Equation 2 for $\tilde{S}$ (for details, see the Appendix C):

$$\tilde{S}_{it} = \begin{cases} Max\left[\left(FV_{it} - \frac{EBIT_{it}(1-\tau)}{\widetilde{WACC}_{it}}\right)\left(\frac{\widetilde{ROIC}_{it} \times \widetilde{WACC}_{it} \times \left(1+\widetilde{WACC}_{it}\right)}{\widetilde{EGR}_{it} \times EBIT_{it}(1-\tau) \times \left(\widetilde{ROIC}_{it} - \widetilde{WACC}_{it}\right)}\right), 0\right] \\ \text{for } \widetilde{ROIC}_{it} - \widetilde{WACC}_{it} > 0 \\ 0 \text{ else.} \end{cases},$$

(8)

where firm value FV_{it} is the sum of the average market value of equity over trading days of a year and the book value of debt (COMPUSTAT's DATA 9) as of December 31 of the respective year. Equations 4 and 6 provide values for $\widetilde{ROIC}$ and $\widetilde{WACC}$. $\widetilde{EGR}$ is based on the 5-year consensus forecasts by analysts. CRSP and COMPUSTAT deliver the remaining information.

Control variables. Financial data such as leverage, dividend payouts, size, etc. are obtained from COMPUSTAT. COMPUSTAT also provides data on marketing and R&D expenditures. We compute the C4-concentration index by aggregating the market shares of the four largest firms at the two-digit NAICS level. Appendix Table A2 provides further details on the definition and data sources of variables used in our analysis. Note that we do not model stock returns but absolute firm value as a result of a corporate valuation model. For that reason, we are not concerned with different release periods as all information is properly aligned at year-end.

5.2 Descriptive Statistics and Model-free Insights

Table 2 presents the descriptive statistics for our data. Mean CBBE is 56.29. Mean return on invested capital corresponds to .22. Analysts forecast the mean 5-year earnings growth to be .13, on average. The mean cost of capital amounts to .09 during the period 2005-2013. Investors expect that the average firm in our sample has a sustainability period of 14 years during which the firm may enjoy profitable growth (ROIC > WACC). This finding is in line with the conclusion by Rappaport and Mauboussin (2001) that a period of at least 10 years is required for most listed companies to justify their market valuation. Note we also estimate a period of 0 years for 74 out of 491 cases (15%), which reduces the median to 8.4 years. Appendix Table B1 shows the correlation matrix for our model variables. There is no excessive correlation suggesting collinearity issues, which is also supported by variance inflation factors (VIF) statistics below the threshold of 10 and condition indexes below 30 (Greene 2012).

We conduct simple mean-difference tests to generate first insights from a model-free analysis. Table 3 summarizes the results. Here, we build two groups that include observations with low CBBE vs. high CBBE. We then compare the group means for our key performance variables. Panel A shows the results if we split the sample based on the median CBBE. In Panel B, we compare the means between the lowest and highest quartiles in terms of CBBE.

Table 2: Univariate Statistics (2005-2013)

	N	Mean	Median	Std. Dev.
Firm value ($m)	3,588	32,074.90	10,419.69	61,456.74
CBBE (0-100)	3,289	56.29	56.68	7.87
Profitability (ROIC)	4,478	.22	.20	.47
Earnings growth (EGR)	3,292	.13	.11	.19
Cost of capital (WACC)	3,364	.09	.09	.03
Sustainability of excess returns (years) [1)]	491	14.04	8.39	18.48
EBIT (1-τ) ($m)	4,514	2,883.66	826.50	6,730.35
Advertising expenditures ($m)	2,593	559.87	162.60	1,104.35
Other expenditures ($m)	4,472	2,658.16	482.86	5,870.54
R&D expenditures ($m)	5,517	435.57	.00	1,394.34
Firm size (ln total assets in $m)	4,522	9.25	9.15	2.10
Financial leverage (ratio)	4,284	2.71	1.11	14.25
Industry concentration (ratio)	5,517	.34	.33	.14
Investment rate (ratio)	4,338	.75	.91	12.57
US GDP growth (ratio)	5,517	.04	.04	.02
Operating margin (ratio)	4,457	.03	.14	4.55
Pretax interest coverage (ratio)	4,133	2.87	.07	93.06
Dividend payout (ratio)	3,882	.51	.14	6.11
Asset growth (ratio)	4,399	.06	.04	.24
Liquidity (ratio)	3,894	1.72	1.44	1.36

[1)] Sustainability is calculated according to Equation 8 using predicted values for ROIC and WACC from Equations 4 and 6. The sample size of these regressions explains the low number of observations for sustainability. For the univariate statistics, we exclude outliers that are more than 6 standard deviations away from the mean (32 cases). 74 out of 491 cases show an expected duration of 0 years.

Results of the difference test provide first evidence in favor of our hypotheses. There are significant differences in terms of firm value, ROIC, earnings growth forecasts, and the sustainability of excess return. Firms with stronger brands enjoy higher firm values, profits, and earnings growth, as well as a longer period of excess return. Unsurprisingly, these differences are more pronounced when we compare the end quartiles of the distribution of CBBE. However, we find no significant differences in the cost of capital.

Table 3: Testing the Differences Between Group Means

	Expected difference	Observations with low CBBE		Observations with high CBBE		Difference (t-statistic)
		N	Mean	N	Mean	
Panel A: Group split based on median CBBE in total sample						
		CBBE = 50.14		CBBE = 62.44		
Firm value	High > Low	1,128	37,058	1,186	47,182	3.397 ***
EBIT (1-τ)	High > Low	1,420	3,684	1,405	4,001	1.051
Profitability (ROIC)	High > Low	1,403	.22	1,393	.27	3.425 ***
Earnings growth (EGR)	High > Low	1,031	.12	1,152	.13	.754
Cost of capital (WACC)	?	954	.09	1,080	.09	1.363
Sustainability of excess returns (S)	High > Low	116	14.22	336	14.16	.026
Panel B: Group split based on highest and lowest sample quartiles for CBBE						
		CBBE = 46.03		CBBE = 65.56		
Firm value	High > Low	581	38,390	637	45,296	1.736 *
EBIT (1-τ)	High > Low	716	3,512	712	3,553	.095
Profitability (ROIC)	High > Low	706	.21	705	.30	3.919 ***
Earnings growth (EGR)	High > Low	506	.11	606	.14	2.888 ***
Cost of capital (WACC)	?	507	.09	543	.09	.909
Sustainability of excess returns (S)	High > Low	46	10.64	185	15.41	1.802 **

Notes: The test for differences between group means is based t-tests that correct for unequal group variances if necessary. Tests are one-sided if clear directional effects are expected, two-sided if not. Sample sizes differ depending on the available observations for focal variables. *** p < .01; ** p < .05; * p < .1.

5.3 Estimation Issues

We use a two-step simulated maximum likelihood approach with instrumental variables (IVs) for estimation (Fischer et al. 2010). Under the usual regularity conditions, this estimator is consistent and asymptotically normal distributed. We use instrumental variables in Equations 4-7 to reduce the danger of biased estimates that may result from a potential simultaneity between CBEE and the drivers of firm value. It is possible that firms anticipate investors' expectations for ROIC, as example, that in turn influences their current investments in CBBE to meet these expectations.

Identification. IV estimation requires that we have sufficient and appropriate instruments available to identify CBBE. Except for CBBE and the lagged dependent variable, we treat all other predictors in an equation as predetermined variables, which we test for, and thus as a potential instrument. To properly identify CBBE we need to use information outside the equation. Equation 3 provides this information. Here, we assume that CBBE in year *t* results from prior investments in advertising, R&D, and other activities. Brand investments are also likely to be higher the larger previous year's earnings and operating margin are. Since CBBE enters the value driver equations 4-7 with a lag of one year we use two-years lagged values of the predictors of Equation 3 (excluding lagged CBBE) as instruments (see also Appendix Table B2 for details).

Validity and strength of instruments. IV estimation rests on the assumption that the exclusion restriction holds. Though there is no absolute certainty about this we can employ several tests to support this assumption. Specifically, we apply three tests to check for the validity and strength of our instruments. Details about the instruments used and test results for each estimation equation are provided in Appendix Table B2.

We first apply the Hausman-Wu test (Greene 2012) to check whether the predetermined variables in Equations 4 to 7 can be treated as exogenous. The test does not reject the exogeneity assumption for these variables. We also test for the exogeneity of CBBE itself. These tests suggest that CBBE is endogenous in the expected ROIC equation ($p < .05$) but not necessarily in the other value driver equations ($p > .05$). To be conceptually consistent, however, we treat CBBE as endogenous across all equations.

Second, we apply the Hausman-Sargan specification test (Greene 2012) to check whether the overidentifying restrictions associated with the outside instruments hold. We have up to six potential overidentifying variables available (see Appendix Table B2 again). The test is not rejected for any equation ($p > .40$). Only two variables, two-periods lagged industry concentration and firm size, do not pass the test in the WACC equation. Consequently, we use the remaining variables to identify this equation.

Third, we test the strength of our instruments by applying the Angrist-Pischke multivariate F test (Greene 2012). Our outside instruments always exceed the threshold of 10 and do not signal weak instrument issues. To summarize, the various tests provide strong evidence for the validity and strength of our instruments.

Finally, we note that estimation of the carryover coefficient associated with the lagged dependent variables in Equations 3 to 7 may cause identification problems (Arellano 2003). The lagged dependent does not only accommodate dynamic effects but also tends to pick up firm heterogeneity. Following Fischer and Albers (2010), we instrument the lagged values with their deviations from the firm-specific mean to isolate the true carryover effect. Note that the endogeneity issue associated with the lagged dependent variable in a fixed effects model does not apply since we do not estimate fixed effects models but models with a random intercept

6 Empirical Results

6.1 Parameter Estimates Related to CBBE

Table 4 summarizes the estimations results for Equations 3-6 on CBBE, expected ROIC, expected earnings growth, and expected WACC. Table 5 shows the results for the sustainability of excess return equation 7, which we estimate via a hazard model approach. Pseudo R^2 ranges from .65 (WACC equation) to .91 (CBBE equation). We consider an $R^2 >$ .50 to be meaningful for explaining variance in a large panel data set. All equations reveal strong heterogeneity of firms as is reflected in the significant standard deviation of the intercept term. This suggests there are indeed important firm-specific factors such as management quality or other market-based assets that we effectively control for. In addition, we find moderate to strong carryover effects across Equations 3 to 6. All significant coefficients of the control variables show the expected direction and are in line with prior empirical studies. For the sake of brevity, we do not discuss these results in detail but turn our focus on the effects associated with CBBE.

6.2 **Elasticity Estimates: Impact on Value Drivers and Firm Value**

An important objective of our study is to understand and compare the relative importance of marketing actions and CBBE for influencing value drivers and ultimately firm value. Few marketers might have an intuition for that. Since parameter estimates are not directly comparable, we transform them into short-term and long-term elasticities. Specifically, we use the conditional estimates of firm-specific parameters (which correspond to the posterior mean in a Bayesian setting) together with firm-specific means for advertising expenditure, CBBE, value drivers, and market value of the firm to compute these elasticities. Appendix D provides details on how we calculate each of the elasticities.

In addition, we report in Appendix G on the Sobel test, which formally tests whether our mediation assumption holds. Except for WACC, we cannot reject this assumption. Moreover, we find support for a full mediation of the impact of CBBE on firm value via the value drivers. We start presenting results for CBBE followed by advertising expenditures.

Table 4: IV-Estimation Results for Equations 3-6

	CBEE (Eq. 3)		*Profitability (Eq. 4)*		*Analyst earnings growth forecast (Eq. 5)*		*Cost of capital (Eq. 6)*	
	Expected sign	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*
Intercept		50.639 (1.09)***		.426 (.022)***		.001 (.083)		.128 (.008)***
Estimated SD		.833 (.073)***		.113 (.012)***		.515 (.061)***		.002 (.006)***
Carryover								
Dependent variable (*t*-1)	+	.295 (.021)***	+	.324 (.001)***	+	.713 (.017)***	+	.279 (.034)***
Marketing constructs								
IV-CBBE (*t*-1)		---	+	.001 ($2.7x10^{-4}$)**	+	.003 (.001)***	+/- [1]	1.109 (.984)
Estimated SD		---		$3.5x10^{-4}$ ($2.1x10^{-4}$)***		.001 ($9.7 x10^{-5}$)***	[1]	.631 (.106)***
Advertising expenditures (*t*-1)	+[2]	.413 (.061)***	+/-[1]	.035 (.018)*	+/-[1]	.302 (.044)***		---
Estimated SD		.446 (.004)***		---		---		---
Controls								
R&D expenditures (*t*-1)	+/-[2]	-.006 (.026)	+/-[1]	-.056 (.012)***	+/-[1]	.166 (.035)***		---
Other expenditures (*t*-1)	+[2]	.050 (.028)***	+/-[1]	.009 (.003)***	+/- [1]	.002 (.010)		---
Operating margin (*t*-1)	+	1.316 (.389)***		---		---	-	-.028 (.008)***
Earnings (*t*-1) [1]	+	1.345 (.389)***		---	+/-	-.005 (.002)***		---
Negative earnings dummy (*t*-1)		---		---	+	.108 (.022)***		---
Financial leverage (*t*-1) [1]		---	+	.182 (.069)***	+/-	-1.632 (5.60)	+/-	-.997 (.588)*
Profitability (*t*-1)		---		---	+	.037 (.045)		---
Investment rate (*t*-1) [1]		---		---	+	-4.37 (24.4)		---
Pretax interest coverage (*t*-1) [1]		---		---		---	-	.001 (.001)
Dividend payout (*t*-1)[1]		---		---		---	+	-2.821 (11.3)
Asset growth (*t*-1)		---		---		---	-	.005 (.003)
Liquidity (*t*-1) [1]		---		---		---	+	7.023 (7.20)
US GDP growth (*t*-1)		---	+/-	.065 (.095)	+/-	-.022 (.477)		---
Observed firm and market heterogeneity								
Firm size (*t*-1)	+/-	-.303 (.058)***	+/-	-.020 (.001)***	-[1]	2.990 (55.7)	-	-.003 (.001)***
Industry concentration (*t*-1)	+/-	-2.408 (.642)***	+/-	-.097 (.017)***	+/-	-.096 (.060)	+/-	-.026 (.006)***
Sample size		1,317		1,084		979		649
Pseudo R^2		.907		.867		.667		.652

Notes: Two-sided t-tests. Pseudo R^2 measures the squared correlation between actual and predicted values of the dependent variable *** p < .01; ** p < .05; * p < .1.
[1] For reading convenience, coefficients are multiplied by 10,000. [2] Variable is log-transformed

Table 4: IV-Estimation Results for Sustainability of Excess Returns (Eq.7)

	Expected sign	*Coefficient (Standard Error)*
Intercept		.961 (.300)***
Estimated SD		1.19 (.233)***
Marketing constructs		
IV-CBBE (*t*-1)	+	.011 (.004)***
Estimated SD		.005 (3.9×10^{-4})***
Advertising expenditures (*t*-1) [1)]	+/-	-.229 (.232)
Controls		
R&D expenditures (*t*-1) [1)]	+	-.246 (.154)
Other expenditures (*t*-1) [1)]	+/-	-.260 (.030)***
Asset growth (*t*-1)	+	.265 (.091)***
US GDP growth (*t*-1)	+/-	7.96 (.880)***
Observed firm and market heterogeneity		
Firm size (*t*-1)	+/-	.111 (.026)***
Industry concentration (*t*-1)	+/-	-.085 (.181)
Weibull scale parameter 1/p		.460 (.013)***
Sample size		417
Log Likelihood		-467.5
Pseudo R^2		.680

Notes: Two-sided t-tests. *** $p < .01$; ** $p < .05$; * $p < .1$. [1)] For reading convenience, coefficients are multiplied by 10,000.

CBBE effects. Table 6 shows the effects of CBBE on value drivers in Panel A and on firm value via the value drivers in Panel B. When applicable we differentiate between short-term and long-term effects. We divide the short-term effect by (1 – carryover) to obtain the long-term effect. As we already explained, there is no carryover in the sustainability of excess return equation. The derived elasticity therefore relates to the long-term effect. Though we do not estimate the effect of CBBE on the earnings level directly, we can infer the effect from our earnings growth equation (see Appendix D again). We do not consider a long-term effect here because the accumulation of earnings due to a change in CBBE is already captured by the estimated effect on earnings growth. In our discussion, we now focus on long-term effects.

Panel A demonstrates that CBBE has, on average, a substantial influence on all value drivers, except for WACC. The largest elasticities are associated with earnings growth (=1.78, $p < .01$) and sustainability of excess returns (=1.22, $p < .01$). Thus, an increase in CBBE translates into a highly elastic response of these two value drivers. The effects are inelastic for profitability (=.17, $p < .01$) and capital cost (=.04, $p > .05$), whereas the average elasticity for capital cost is not significantly different from zero. Note the elasticity does not only depend on the firm-specific parameter for CBBE but also on the level of CBBE and the respective value driver.

In Panel B, we show CBBE elasticities with respect to firm value. These elasticities reveal the ultimate effect of a change in CBBE on firm value that is mediated by a value driver. Note these elasticities cannot be interpreted as sales elasticities because the dependent variable, firm value, is a profit measure. Edeling and Fischer (2016) demonstrate that the range of firm value elasticities is much larger and frequently includes negative values. A negative elasticity occurs if a firm is overinvested in an intermediate performance variable, such as CBBE. Put differently, there exists an optimal level for CBBE and that level depends on various parameters including the effectiveness of CBBE in driving a value driver.

The picture for the firm value elasticities corresponds with the value driver elasticities, but they are considerably smaller. Again, the average elasticity associated with earnings growth (=.91, $p < .01$) and sustainability of excess returns (=.50, $p < .01$) are highest though they are no longer elastic. The average elasticity for profitability (=.03, $p < .01$) is much lower. It turns negative for cost of capital (-.07, $p > .05$), but is again insignificant. We also present the total firm value elasticity with respect to CBBE in the last row of Table 6. Based on our valuation formula (3), this effect considers the simultaneous and potentially synergetic impact of CBBE on firm value via all value drivers. The elasticities are .29 ($p < .01$, short-term) and 1.58 ($p < .01$, long-term). Edeling and Fischer (2016) find an elasticity of .75 for perceptual brand metrics in their meta-analysis, which provides strong external support for our estimated range of values.

Advertising effects. We now turn our focus on advertising investments as one of the major drivers of CBBE. Table 7 shows all elasticity-based effects on value drivers in Panel A and on firm value in Panel B. Again, we focus on long-term elasticities in our discussion.

The first and most striking difference to CBBE elasticities in Table 6 is that elasticities are, on average, much smaller and close to zero. This observation, however, is consistent with the meta-analysis by Edeling and Fischer (2016), which also reports advertising elasticities to be much lower than marketing-asset elasticities. The major argument by the authors is that firms are more experienced in optimizing marketing expenditures and are, on average, close to the optimal level. In the optimum, the marginal effect on profit or firm value, respectively, must equal zero.

Comparing the effects by value drivers (see Panel A) reveals again that the impact of advertising investments in CBBE is, on average, highest on earnings growth (=.01, $p < .01$) and sustainability of excess return (=.02, $p < .01$). The average effect on profitability is considerably lower (=.001, $p < .01$). It is not significant with respect to cost of capital (=1.4x10-5, $p > .05$).

Panel B shows the advertising elasticities with respect to firm value mediated by the respective value driver. We find again the largest impact on firm value via earnings growth (=.01, $p < .01$) and sustainability of excess returns (=.01, $p < .01$), followed by profitability (=3.1x10-4, $p < .01$). The impact via cost of capital is, on average, insignificant (=2.9x10-5, $p > .05$). When we consider all value drivers simultaneously, the average firm value elasticity with respect to advertising investment in CBBE amounts to .003 ($p < .01$) in the short run and

.02 ($p < .01$) in the long run. For comparison, the average advertising elasticity in Edeling and Fischer's meta-analysis is .04.

Heterogeneity across industries. Finally, we study differences across industries. Following the Global Industry Classification Standard (GICS), we assign firms to five industry sectors: consumer discretionary, consumer staples, information technology and telecommunications, and industrials and others (e.g., transportation). We apply ANOVA to check whether there are significant differences in the firm value effects. Our focus is on (long-term) firm value elasticities with respect to CBBE that is mediated by the firm value drivers (see Table 8). More details on advertising effects and at lower aggregation levels can be found in Appendix D.

Table 8 reveals there is a significant variation of firm value elasticities across industries as supported by the F-statistics. The only exception is the effect via ROIC. Here, an investment in CBBE improves ROIC and ultimately firm value, but this is not different for industries. Firm value elasticities with respect to current earnings strength (EBIT, =.172), earnings growth (=3.22), and sustainability of excess returns (=.713) are highest for the sector of industrials & others. This sector includes materials, energy, utility, and transportation firms. Consumer discretionary firms follow in terms of elasticity sizes for these value drivers. Consumer staples and IT & telecommunication firms show the lowest firm value elasticities.

Interestingly, the CBBE-firm value effect via WACC is very different across industry sectors. Further strengthening the brand increases firm value for consumer staples (=1.60) and industrials & others (=.199), but it destroys value for consumer discretionary (=-.955) and IT & telecommunications (=-.737). The major reason for this negative effect is the positive impact of the brand on capital cost.

As a result of these differences in value driver mediated firm value elasticities, the overall effect of CBBE on firm value is also very different across the industry sector. Here again, industrials & others (=3.84) and consumer discretionary firms (=2.25) show the largest elasticities, followed by IT & telecommunications (1.16) and consumer staples (=.448).

6.3 **Robustness Checks**

We performed several additional analyses and robustness checks. Specifically, we tested how sensitive our results and conclusions are with respect to the distributional assumptions of $\tilde{S}$, the omission of other market-based assets such as customer strength, the specification of dynamics in the models, the use of alternative estimation approaches, the stability of the CBBE parameter over time, and the composition of the sample. For the sake of brevity, we do not report on these robustness checks here but refer to the Appendix for full details (section H with Figure H1 and Tables H1-H8).

We obtain large consistency with and support for our focal model results. Hence, we conclude that our results are not driven by model assumptions, omission of important variables, model specifications, the selection of estimation approaches, and the composition of the sample.

Table 6: Elasticities of Value Drivers and Firm Value With Respect to CBBE

(Based on Distribution of Firm-Specific Elasticity Estimates)

Panel A: CBBE effect on value drivers

	Short-term effect					**Long-term effect**				
	Mean	*Median*	*# Firms*	*Positive effects (%)*	*Negative effects (%)*	*Mean*	*Median*	*# Firms*	*Positive effects (%)*	*Negative effects (%)*
Current earnings (EBIT)	.069 ***	.087	231	74	26	- -	-	-	-	-
Profitability (ROIC)	.116 ***	.139	246	78	22	.172 ***	.205	246	78	22
Earnings growth forecasts (EGR)	.510 ***	.866	230	74	26	1.776 ***	3.017	230	74	26
Capital cost (WACC)	.026	.076	146	63	37	.035	.105	146	63	37
Sustainability of excess returns (S)	-	-	-	-	-	1.220 ***	1.242	126	98	2

Panel B: CBBE effect on firm value mediated by value drivers

	Short-term effect					**Long-term effect**				
	Mean	*Median*	*# Firms*	*Positive effects (%)*	*Negative effects (%)*	*Mean*	*Median*	*# Firms*	*Positive effects (%)*	*Negative effects (%)*
Current earnings (EBIT)	.069 ***	.087	231	74	26	- -	-	-	-	-
Profitability (ROIC)	.023 ***	.022	123	89	11	.033 ***	.033	123	89	11
Earnings growth forecasts (EGR)	.263 ***	.137	120	73	26	.914 ***	.476	120	73	28
Capital cost (WACC)	-.051	-.174	126	44	56	-.070	-.242	126	44	56
Sustainability of excess returns (S)	-	-	-	-	-	.496 ***	.520	125	96	4
Total effect [1]	.293 ***	.264	121	66	34	1.578 ***	1.108	121	79	21

[1] The total effect simulates the simultaneous effect of CBBE on firm value via all value drivers.

Notes: All elasticity calculations are based on firm-specific estimates. We exclude extreme outlier values that are more than 6 standard deviations away from the mean. The number of outliers ranges from 1 to 5.

Significance results are based on two-sided t-tests; *** p < .01; ** p < .05.

Table 7: Elasticities of Value Drivers and Firm Value With Respect to Advertising Investment in CBBE

(Based on Distribution of Firm-Specific Elasticity Estimates)

Panel A: Advertising investment in CBBE effect on value drivers

	Short-term effect					**Long-term effect**				
	Mean	*Median*	*# Firms*	*Positive effects (%)*	*Negative effects (%)*	*Mean*	*Median*	*# Firms*	*Positive effects (%)*	*Negative effects (%)*
Current earnings (EBIT)	.001 ***	3.0x10^{-4}	227	66	34	- -	-	-	-	-
Profitability (ROIC)	.001 ***	.001	242	72	28	.001 ***	.001	242	72	28
Earnings growth forecasts (EGR)	.003 **	.003	226	65	35	.010 **	.011	226	65	35
Capital cost (WACC)	1.0x10^{-5}	4.6x10^{-4}	143	59	41	1.4x10^{-5}	.001	143	59	41
Sustainability of excess returns (S)	-	-	-	-	-	.017 ***	.017	123	93	7

Panel B: Advertising investment in CBBE effect on firm value mediated by value drivers

	Short-term effect					**Long-term effect**				
	Mean	*Median*	*# Firms*	*Positive effects (%)*	*Negative effects (%)*	*Mean*	*Median*	*# Firms*	*Positive effects (%)*	*Negative effects (%)*
Current earnings (EBIT)	.001 ***	3.0x10^{-4}	227	66	34	- -	-	-	-	-
Profitability (ROIC)	2.1x10^{-4} ***	1.7x10^{-4}	121	83	17	3.1x10^{-4} ***	2.5x10^{-4}	121	83	17
Earnings growth forecasts (EGR)	.002 ***	4.7x10^{-4}	117	67	33	.008 ***	.002	117	67	33
Capital cost (WACC)	2.1x10^{-5}	-3.0x10^{-4}	123	46	54	2.9x10^{-5}	-4.1x10^{-4}	123	46	54
Sustainability of excess returns (S)	-	-	-	-	-	.007 ***	.007	122	92	8
Total effect [1)]	.003 ***	.001	117	60	40	.017 ***	.009	117	74	26

[1)] The total effect simulates the simultaneous effect of advertising investment in CBBE on firm value via all value drivers.

Notes: All elasticity calculations are based on firm-specific estimates. We exclude extreme outlier values that are more than 6 standard deviations away from the mean. The number of outliers ranges from 1 to 5.

Significance results are based on two-sided t-tests; *** $p < .01$; ** $p < .05$.

Table 8: Elasticities of Value Drivers and Firm Value With Respect to CBBE by Industry

		Long-term CBBE effect on firm value mediated by value drivers										*Total long-term CBBE effect on firm value*	
		CBBE → EBIT → Firm value [2)]		CBBE → ROIC → Firm value		CBBE → EGR → Firm value		CBBE →WACC → Firm value		CBBE → S → Firm value			
Industry	Company brand examples	# firms	Marginal mean	# firms	Marginal mean	# firms	Marginal mean	# firms	Marginal mean	# firms	Marginal mean	# firms	Marginal mean
Consumer Discretionary	GM, Nike, Sony, Hilton, Saks	91	.090	102	.033	92	1.367	63	-.955	50	.620	49	2.254
Consumer Staples	Safeway, Walmart, Coca-Cola, Gillette	47	-.006	50	.022	47	.040	34	1.597	33	.446	32	.448
IT & Telecommunications	Google, HP, AT&T, Verizon	40	.092	40	.023	39	.617	27	-.737	22	.254	20	1.161
Industrials & Others [1)]	Ashland, BP	22	.172	23	.044	22	3.221	14	.199	13	.713	13	3.844
Grand mean		231	.074***	123	.032***	120	.797***	126	.029	125	.457***	121	1.34***
F-value			4.03***		.166		6.53**		5.76***		5.84***		7.70***

[1)] Includes brands from GICS categories Transportation, Materials, Energy, and Utility.
[2)] CBBE effect on current earnings strength (EBIT) is a short-term effect per definition.
[3)] We do not report values for Health Care and Financial Services since the number of elasticity estimates is too small to infer substantial conclusions (N ≤ 8 for WACC, S, and firm value elasticities). We report a more detailed split including all industries in Appendix D.
Notes: *** p < .01; ** p < .05; EBIT = current earnings strength, ROIC = profitability, EGR = earnings growth forecasts, WACC = cost of capital, S = sustainability of excess returns.

7 Conclusion and Limitations

Firm value is strongly driven by investors' expectations about the rate of return on new invested capital, the future growth in earnings, the cost of capital, and the length of the period during which a firm can sustain competitive advantage. We investigated the role of CBBE and advertising investments in CBBE in driving firm value via these four value drivers.

Our empirical analysis helps answering our research questions. Tables 6 to 8 provide answers on the relative impact of CBBE and advertising investment on the value drivers and on firm value. From these results, we conclude that the most influential route of value generation for brands is via improving earnings growth expectations and increasing the expected period of excess returns. Advertising investments in CBBE do pay off in firm value, on average. The associated elasticity, however, is close to zero suggesting firms are, on average, close to their optimal level. Our findings have the following implications for researchers and managers.

7.1 Implications for Researchers

By estimating firm-value effects of CBBE via different value drivers, we contribute to our understanding of the role of brands for value generation. Based on the rich brand literature, most scholars probably agree that brands improve each of the four value drivers. However, the relative magnitude of these effects is not well understood. There are probably two surprising conclusions from our results. First, there is no unidirectional relation between brands and WACC. Second, although we have good arguments for a strong relationship between brands and profitability, e.g., price premiums and marketing efficiency advantages, the impact is only small. How can this result be explained? We believe that strong brands do have this potential, but they also require investments at a constantly high level to sustain their strength. Investors seem to factor such resource commitment into their brand-driven profitability expectations.

Our analysis also has implications for the discussion of the role of brands for capital cost. Recall there is no general brand effect on capital cost and thus firm value, which reflects the more or less equal number of positive and negative elasticities (see Table 6, Panel B again). This finding contradicts with findings from prior studies (e.g., Rego et al. 2009). However, it does not mean that these studies are wrong. They simply focused on separate components of WACC, such as systematic risk or credit ratings. Our analysis completes the picture and suggests that the ultimate impact of brands on WACC is very much depending on market and firm characteristics.

We emphasize that our empirical study extends our knowledge about the drivers of sustainable competitive advantage. Based on the valuation model, we suggest an innovative way to measure sustainability of excess return that is implicitly incorporated in the market capitalization of firms. Consistent with the imperative that marketing is to build unique, non-substitutable, and valuable assets (Srivastava et al. 1998), we conclude that a strong brand is a key source for maintaining sustainable competitive advantage.

The finding that brand impact is largest on earnings growth and sustainability of excess returns offers two important conclusions. First, investors seem to predominantly perceive the value of brands in their ability to generate business from expanding into new markets and acquiring new customers. This is probably the key feature that distinguishes the brand from customer assets, where value is generated via stable cash flows from the base of existing customers (Rust et al. 2004). Second, investors also seem to appreciate the ability of brands to build a sustainable competitive advantage, which provides a powerful shield against competitive attacks. Securing high profitability that exceeds capital cost is more relevant to investors than the direct impact of brands on profit margins (Ghesquieres et al. 2016).

Finally, we note that our findings might also advance the thinking about brand valuation. There is still no consensus on the method for brand valuation. Leading commercial vendors such as Interbrand consider the impact of brands on capital cost as an important factor in their methodology. However, our results do not support this. They rather emphasize growth of the business and competitive advantage as relevant brand-related drivers in the valuation. A recent survey among investment managers underlines the practical importance of this aspect: investment managers are rather looking for credible strategies for value-creating growth than for excess cash-payouts by firms (Ghesquieres et al. 2016). Thus, the findings from this study might stimulate the development and refinement of brand valuations methods.

7.2 **Implications for Managers**

Our results offer the potential to advance management practice in several ways. First, we extend prior research on the value relevance of brands by opening the black box and providing insights into the sources of value creation. Marketing managers benefit from these insights because it helps them telling a compelling story about the value growth potential of marketing investments. The use of short-term product-market outcomes as a yardstick for brand performance can interact in unfortunate ways with the tenure of a brand manager. Our study instead provides marketing executives with a richer story to communicate the path of firm value growth that is backed up with strong empirical evidence.

In addition, CEOs and CFOs can improve their communication with the investor community. The key is to stay with the mental model of investors who think about ROIC, earnings growth, and the sustainability of excess returns. Investors are especially looking for companies, which use their resources to improve the fundamental value of their business. They see growth as a top priority for management. The new quality in this communication is to demonstrate how exactly brand investments impact future firm value and growth expectations.

Second, our study reveals significant differences of brand-related value generation across industries. It appears that the potential for value generation is highest for the group of industrials & others, i.e. for typical B2B firms. While not unexpected, this finding emphasizes that brands indeed play an important role for B2B customers and investors. Our elasticity estimates help B2B brand managers quantify the potential growth in firm value due to brand investments that are not limited to advertising.

Based on the industry analysis, we also conclude that brand investments are probably close to their optimum for consumer staples, i.e. FMCG firms such as Coca-Cola and P&G. But firms in the consumer discretionary sector such as GM or Nike are still show potential for further brand investments to grow firm value. Hence, consumer businesses are not saturated, yet.

Third, our framework helps financial constituencies to think differently about their investment decisions. Investors gain a better understanding of how marketing impacts their key metrics. Since our model conceptualizes and quantifies the routes of future cash flow generation, financial analysts may use the empirical estimates as a reference point in their valuation models. Our elasticity estimates are particularly actionable for them.

Finally, our study could change how brands are strategically managed. Investors obviously understand that the value contribution of brands primarily arises from earnings growth and sustainability of excess returns. This suggests that they might also expect brand management to focus on these dimensions. As a consequence, strategic brand management decisions should reflect these expectations by leveraging the brand extension potential and sharpening the competitive distinctiveness of the brand.

Our study has limitations that may stimulate further research. First, our study focuses on one important market-based asset, the brand. We effectively control for other assets and test the robustness of our results. It would, however, be interesting to study the role of customer satisfaction, service quality, etc. in future work. Second, we use the Harris EquiTrend metric to measure CBBE, which has been done in prior work (e.g., Bharadwaj et al. 2011). Strictly speaking, our results hold true only for this measure. There are other CBBE metrics (e.g., Luo et al. 2012; Stahl et al. 2012) and it would be interesting to replicate our models with these metrics. Finally, we acknowledge that brands might also have a direct impact on firm value and/or growth expectations that is not covered by their impact on the four value drivers. Following the idea of Joshi and Hanssens (2010), future research could study such a direct route in more depth.

References Paper III

Aaker, David A. and Robert Jacobson (2001), "The Value Relevance of Brand Attitude in High-Technology Markets," *Journal of Marketing Research*, 38 (4), 485-493.

Ailawadi, Kusum L., Donald R. Lehmann, and Scott A. Neslin (2003), "Revenue Premium as an Outcome Measure of Brand Equity," *Journal of Marketing*, 67 (4), 1–17.

Arellano, Manuel (2003), *Panel Data Econometrics*. Oxford: Oxford University Press.

Bharadwaj, Sundar G., Kapil R. Tuli, and Andre Bonfrer (2011), "The Impact of Brand Quality on Shareholder Wealth", *Journal of Marketing*, 75 (5), 88-104.

Barth, Mary E., Michael B. Clement, George Foster, and Ron Kasznik (1998), "Brand Values and Capital Market Valuation," *Review of Accounting Studies*, 3 (1), 41–68.

Chaudhuri, Arjun and Morris B. Holbrook (2001), "The Chain of Effects from Brand Trust and Brand Affect to Brand Performance: The Role of Brand Loyalty," *Journal of Marketing*, 65 (2), 81-93.

Choi, In (2001), "Unit Root Tests for Panel Data," *Journal of International Money and Finance*, 20, 249-272.

Christen, Markus, Sachin Gupta, John C. Porter, Richard Staelin, and Dick R. Wittink (1997), "Using Market-Level Data to Understand Promotion Effects in a Nonlinear Model," *Journal of Marketing Research*, 34 (3), 322-334.

Copeland, Thomas E., John F. Weston, and Kuldeep Shastri (2013), *Financial Theory and Corporate Policy*. 4th ed. New Jersey: Pearson.

Damodaran, Aswath (2012), *Investment Valuation: Tools and Techniques for Determining the Value of Any Asset*. 3rd ed. New Jersey: Wiley.

Demsetz, Harold (1982), "Barriers To Entry," *American Economic Review*, 72 (1), 47.

Dierickx, Ingemar and Karel Cool (1989), "Asset Stock Accumulation and Sustainability of Competitive Advantage," *Management Science*, 35 (12), 1504-1511.

Edeling, Alexander and Marc Fischer (2016), "Marketing's Impact on Firm Value: Generalizations from a Meta-Analysis", *Journal of Marketing Research*, 53(4), 515-534.

Erickson, Gary and Robert Jacobson (1992), "Gaining Comparative Advantage Through Discretionary Expenditures: The Returns to R&D and Advertising," *Management Science*, 38 (9), 1264–1279.

Fama, Eugene F. (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work," *The Journal of Finance*, 25 (2), 383–417.

Fischer, Marc and Sönke Albers (2010), "Patient- or Physician-Oriented Marketing: What Drives Primary Demand for Prescription Drugs?" *Journal of Marketing Research*, 47 (1), 103-121.

Fischer, Marc and Alexander Himme (2017), "The Financial Brand Value Chain: How Brand Investments Contribute to the Financial Health of Firms," *International Journal of Research in Marketing*, forthcoming.

Fischer, Marc, Peter S. H. Leeflang, and Peter C. Verhoef (2010), "Drivers of Peak Sales for Pharmaceutical Brands," *Quantitative Marketing and Economics*, 8 (4), 429-460

Ghesquieres, Julien, Jeffrey Kotzem, Tim Nolan, Frank Plaschke, and Hady Farag (2016), "In a Tough Market, Investors Seek New Ways to Create Value," *BCG Perspectives*, May 2016.

Greene, William H. (2012), *Econometric Analysis.* 7th ed. Upper Saddle River, NJ: Pearson.

Hanssens. Dominique M., Leonard J. Parsons, and Randall L. Schultz (2001), *Market Response Models: Econometric und Time Series Analysis*. 2nd. ed. Boston: Kluwer Academic Publishers.

Himme, Alexander and Marc Fischer (2014), "Drivers of the Cost of Capital: The Joint Role of Non-Financial Metrics," *International Journal of Research in Marketing*, 31 (2), 224-238.

Joshi, Amit and Dominique M. Hanssens (2010), "The Direct and Indirect Effects of Advertising Spending on Firm Value", *Journal of Marketing*, 74 (1), 20–33.

Katsikeas, Constantine S., Neil A. Morgan, Leonidas C. Leonidou, and G. Tomas M. Hult (2016), "Assessing Performance Outcomes in Marketing," *Journal of Marketing*, 80 (2), 1-20.

Keller, Kevin L. (1993), "Conceptualizing, Measuring, and Managing Customer-Based Brand Equity," *Journal of Marketing*, 57 (1), 1–22.

Koller, Timothy, Marc Goedhart, and David Wessels (2015), *Valuation.* 6th ed. Hoboken, New Jersey et al.: Wiley.

Kothari, S. P. (2001), "Capital markets research in accounting," *Journal of Accounting and Economics*," 31 (1-3), 105–231.

Lane, Vicki and Robert Jacobson (1995), "Stock Market Reactions to Brand Extension Announcements: The Effects of Brand Attitude and Familiarity," *Journal of Marketing*, 59(1), 63-77.

Makadok, Richard (2001), "Toward a Synthesis of the Resource-Based View and Dynamic-Capability Views of Rent Creation," *Strategic Management Journal*, 22 (5), 387–401.

Mela, Carl, Sunil Gupta, and Donald R. Lehmann (1997), "The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice," *Journal of Marketing Research*, 34 (2), 248–261.

Mizik, Natalie (2014), "Assessing the Total Financial Performance Impact of Brand Equity with Limited Time-series Data," *Journal of Marketing Research*, 51(6), 691-706.

———, and Robert Jacobson (2008), “The Financial Value Impact of Perceptual Brand Attributes,” *Journal of Marketing Research*, 45 (1), 15–32.

Morgan, Neil A., Rebecca J. Slotegraaf, and Douglas W. Vorhies (2009), “Linking marketing capabilities with profit growth,” *International Journal of Research in Marketing*, 26 (4), 284–293.

Rappaport, Alfred and Michael J. Mauboussin (2001), *Expectations investing: Reading stock prices for better returns*. Boston: Harvard Business School Press.

Rego, Lopo L., Matthew T. Billett, and Neil A. Morgan (2009), “Consumer-Based Brand Equity and Firm Risk,” *Journal of Marketing*, 73 (6), 47–60.

Rust, Roland T., Katherine N. Lemon, Valarie A. Zeithaml (2004), “Return on Marketing: Using Customer Equity to Focus Marketing Strategy,” *Journal of Marketing*, 68 (1), 109-127.

Srinivasan, Shuba and Dominique M. Hanssens (2009), “Marketing and Firm Value: Metrics, Methods, Findings, and Future Directions,” *Journal of Marketing Research*, 46 (3), 293–312.

Srivastava, Rajendra K., Tasadduq A. Shervani, and Liam Fahey (1998), “Market-Based Assets and Shareholder Value: A Framework for Analysis*,” Journal of Marketing*, 62 (1), 2–18.

Stahl, Florian, Mark Heitmann, Donald R. Lehmann, and Scott A. Neslin (2012), “The Impact of Brand Equity on Customer Acquisition, Retention, and Profit Margin,” *Journal of Marketing*, 76 (4), 44-63.

Titman, S., & Wessels, R. (1988). The Determinants of Capital Structure Choice. *Journal of Finance*, 43(1), 1–19.

Tuli, Kapil R. and Sundar G. Bharadwaj (2009), “Customer Satisfaction and Stock Returns Risk,” *Journal of Marketing*, 3 (6), 184-197.

Appendix Paper III

Appendix A: Correlation Matrix, Overview of Symbols, and Variable Definitions

Table A1
OVERVIEW OF SYMBOLS

Variables	
ADV	Advertising expenditures
CBBE	Customer-based brand equity
CONC	Industry concentration
DIV	Dividend payout
EARN	Earnings less tax and before interest (net operating profit less tax)
EBIT	Earnings before interest and tax
EGR	Earnings growth rate
FV	Firm value
GDPGR	Growth rate of the US gross domestic product
A_GROWTH	Asset growth
I	Investments in new capital
INT	Pretax interest coverage
IR	Investment rate
LEV	Financial leverage
LIQ	Liquidity
D_NEARN	Dummy for negative earnings in preceding year (1 = negative)
OE	Other expenditures
OPM	Operating margin
ROIC	Return on invested capital
RD	R&D expenditures
S	Sustainability of excess returns
SIZE	Firm size
WACC	Weighted average cost of capital
τ	Cash tax rate
$\widetilde{[\dots]}$	Expected realization of a variable
Indexes	
i	Firm index with i = 1,… *I* (number of firms)
t	Time index with t = 1,… *T* (number of periods)
Model parameters	
a, b, c, d, g	Regression parameters to be estimated
u, φ, η	Error terms
σ^2	Variance
ψ	Variance-covariance matrix of random parameters
$f(\tilde{S})$	Density function of expected sustainability of excess returns
λ	Location parameter of survival function for $\tilde{S}$
p	Scale parameter of survival function for $\tilde{S}$
ε	Elasticity

Table A2
VARIABLE DEFINITIONS AND MEASURES

Variables	Definition	Measure	Source / COMPUSTAT
Firm value (FV)	Market capitalization of equity + preferred stock + book value of debt + minority interest	(Yearly average of monthly stock prices · outstanding shares) + preferred stock + total Liabilities	CRSP (market capitalization equity) + DATA 10 (Preferred stock); DATA 5 (Current Liabilities) + DATA 9 (Long-term debt) + DATA 49 (Minority interest)
Customer-based brand equity (CBBE)	Customer-based brand equity	Survey-based index as measure of customer-based brand equity (see Web Appendix W3 for details)	Harris Interactive: Poll EquiTrend
Profitability (ROIC)	Net operating profit after tax / Invested capital	EBIT×(1- τ) / Invested capital	DATA 308 (Operating cash flow), DATA 37 (Invested Capital)
Earnings growth (EGR)	5y-estimates of earnings growth (consensus)	Arithmetic mean across analysts	I/B/E/S
Earnings (EARN)	Net operating profit after tax	EBIT×(1- τ)	DATA 308 (Operating cash flow)
Cost of capital (WACC)	Weighted-average cost of capital	[Equity×cost of equity + debt ×cost of debt×(1-τ)]/Total capital	Bloomberg
Advertising expenditures (ADV)	Advertising expenditures	-	DATA 45 (Advertising)
Other expenditures (OE)	Other marketing expenditures	SG&A expense – non-coordinating costs (advertising, R&D, bad debt expense, provision for doubtful accounts, employee benefit expenses)	DATA 189 (SG&A); DATA 45 (Advertising); DATA 46 (R&D); DATA 67 (Estimated doubtful receivables); DATA 43 (Pension/retirement expense); DATA 215 (Stock options)
R&D expenditures (RD)	R&D expenditures	-	DATA 46 (R&D)
Firm size (SIZE)	Total assets	Log of total assets	DATA 6 (Total assets)
Financial Leverage (LEV)	Book value total debt / Book value equity + preferred stock	-	DATA 5 (Current Liabilities) + DATA 9 (Long-term debt); DATA 60 (Common Equity) + DATA 10 (Preferred stock)
Industry concentration (CONC)	Four-firm concentration index	Cumulative market share of the top four firms in the industry defined by two digits of the NAICS	DATA 12 (Sales)
Investment rate (IR)	(1-cash dividends) / Net operating profit after tax	(1-cash dividends) / [EBIT×(1- τ)]	DATA 21 (Cash dividend); DATA 308 (Operating cash flow)
Operating margin (OPM)	Operating income before depreciation/sales	Operating income before depreciation/sales	DATA 13 (operating income before depreciation); DATA 12 (sales)
Pretax interest coverage (INT)	EBIT divided by interest expense	(Operating income after depreciation + interest expense)/interest expense	DATA 178 (operating income after depreciation); DATA 15 (interest expense)
Dividend payout (DIV)	Cash dividends/earnings	Cash dividends/available income	DATA 21 (cash dividend); DATA 20 (income available for common stockholders)
Asset Growth (A_GROWTH)	Terminal total assets/initial assets	Total assets/total assets$_{t-1}$	DATA 6 (Total assets)
Liquidity (LIQ)	Current ratio	Current assets/current liabilities	DATA 4 (current assets); DATA 5 (current liabilities)
GDPGR	US GDP gross rate	(Real US GDP$_t$ - Real US GDP$_{t-}$)/ Real US GDP$_{t-1}$	Bureau of Economic Analysis (BEA)

Appendix B: Correlation Matrix and Results of Instrument Tests

Table B1

CORRELATION ANALYSIS

	1.	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**	**11.**	**12.**	**13.**	**14.**	**15.**	**16.**	**17.**	**18.**
1. CBBE	1.00 (3289)																	
2. Profitability	.05** (2796)	1.00 (4478)																
3. Earnings growth	.03 (2183)	.40** (3077)	1.00 (3292)															
4. Cost of capital	.04 (2034)	.02 (2998)	.07** (2281)	1.00 (3364)														
5. Sustainability	.08 (452)	-.12* (491)	.02 (491)	.21** (485)	1.00 (491)													
6. Advertising expenditures	.04 (1702)	.04* (2563)	.03 (2055)	-.07** (1727)	-.14** (487)	1.00 (2593)												
7. Other expenditures	.08** (2794)	.02 (4368)	-.05** (3054)	-.08** (2986)	-.13** (487)	.40** (2562)	1.00 (2562)											
8. R&D expenditures	.01 (3289)	.03* (4478)	.00 (3292)	-.03 (3364)	-.14** (491)	.47** (2593)	.35** (2593)	1.00 (4472)										
9. Firm size	-.19** (2826)	.00 (4478)	-.06** (3085)	-.22** (3012)	-.14** (491)	.43** (2593)	.45** (2593)	,304** (4410)	1.00 (4522)									
10. Financial leverage	-.07** (2668)	.01 (4268)	-.02 (2982)	-.08** (2893)	.00 (485)	-.03 (2399)	-.02 (2399)	-.02 (4167)	.03* (4284)	1.00 (4270)								
11. Industry concentration	-.01 (3289)	.03* (4478)	-.05** (3292)	-.04* (3364)	-.07 (491)	.00 (2593)	.07** (2593)	.01 (4472)	.04* (5517)	-.01 (4522)	1.00 (4284)							
12. Investment rate	.02 (2753)	.00 (4295)	.00 (3071)	.01 (2929)	.13** (491)	-.01 (2589)	.00 (2589)	.00 (4232)	-.04** (4338)	.00 (4336)	.01 (4091)	1.00 (4338)						
13. U.S. GDP growth	.04* (3289)	.02 (4478)	.03ü (3292)	-.02 (3364)	.07 (491)	.00 (2593)	-.02 (2593)	-.01 (4472)	-.01 (5517)	.00 (4522)	.05** (4284)	-.02 (5517)	1.00 (4338)					
14. Operating margin	-.02 (2796)	.11** (4412)	-.01 (3044)	-.03 (2987)	-.17** (491)	.03 (2592)	.01 (2592)	.01 (4358)	.07** (4457)	.00 (4456)	.00 (4205)	.00 (4457)	.00 (4279)	1.00 (4457)				
15. Pretax interest coverage	.02 (2607)	.014 (4089)	.00 (2789)	.02 (2742)	.01 (488)	.01 (2282)	-.01 (2282)	.00 (4037)	.00 (4133)	-.01 (4130)	.00 (3879)	.00 (4133)	-.02 (3958)	.00 (4083)	1.00 (4133)			
16. Dividend payout	-.07 (2515)	.00 (3839)	-.01 (3022)	.00 (2636)	.06 (490)	-.01 (2583)	-.01 (2583)	-.01 (3778)	.01 (3882)	.00 (3880)	.01 (3643)	.15** (3882)	.00 (3878)	.00 (3823)	.00 (3507)	1.00 (3882)		
17. Asset growth	.02 (2758)	.03 (4362)	.07** (3033)	.02 (2948)	.15** (491)	-.02 (2511)	.00 (2511)	.00 (4294)	-.02 (4399)	-.01 (4399)	.03* (4164)	-.02 (4399)	.11** (4224)	-.05** (4335)	.01 (4021)	.01 (3770)	1.00 (4399)	
18. Liquidity	.07** (2458)	-.05** (3851)	.03 (2561)	.13** (2588)	.04 (491)	-.15** (2299)	-.12** (2299)	-.01 (3851)	-.25** (3894)	-.07** (3892)	-.06** (3666)	-.01 (3894)	-.01 (3714)	-.10** (3886)	.05** (3720)	-.02 (3266)	.07** (3779)	1.00 (3894)

Table B2. Results of Instrument Tests

	Equation 4 Dependent variable = ROIC			*Equation 5 Dependent variable = EGR*			*Equation 6 Dependent variable = WACC*			*Equation 7 Dependent variable = S*		
	Variable	F-Value	p-value	Variable	F-Value	p-value	Variable	F-Value	p-value	Variable	F-Value	p-value
Hausmann-Wu specification test on exogeneity assumption for predetermined variables	ADV (*t*-1)	.149	.70	ADV (*t*-1)	1.036	.31	LEV (*t*-1)	.006	.94	ADV (*t*-1)	.001	.97
	OE (*t*-1)	.241	.62	OE (*t*-1)	.211	.65	INT (*t*-1)	.644	.42	OE (*t*-1)	1.076	.30
	RD (*t*-1)	.001	.98	RD (*t*-1)	.001	.97	OPM (*t*-1)	.217	.64	RD (*t*-1)	1.132	.29
	LEV (*t*-1)	.654	.42	LEV (*t*-1)	1.635	.20	DIV (*t*-1)	.301	.58	SIZE (*t*-1)	.081	.78
	GDPGR (*t*-1)	.001	.97	EARN (*t*-1)	.360	.55	A_GROWTH (*t*-1)	.175	.68	GDPGR (*t*-1)	.444	.51
	CONC (*t*-1)	2.258	.13	D_NEARN (*t*-1)	3.751	>.05	LIQ (*t*-1)	.048	.83	CONC (*t*-1)	.324	.57
	SIZE (*t*-1)	.298	.59	ROIC (*t*-1)	.318	.57	CONC (*t*-1)	1.557	.21	A_GROWTH (*t*-1)	1.103	.29
				IR (*t*-1)	.002	.96	SIZE (*t*-1)	.331	.57			
				GDPGR (*t*-1)	.401	.53						
				CONC (*t*-1)	2.137	.14						
				SIZE (*t*-1)	1.147	.28						
Hausmann-Wu specification test on exogeneity assumption for focal CBBE measure		4.476	.03		.590	.44		2.430	.12		2.375	.12
Hausman-Sargan specification test on overidentifying restrictions: outside instruments and test results	*Endogenous*: CBBE			*Endogenous*: CBBE			*Endogenous*: CBBE			*Endogenous*: CBBE		
	Exogenous:			*Exogenous*:			*Exogenous*:			*Exogenous*:		
	ln ADV (*t*-2)			ln ADV (*t*-2)			ln ADV (*t*-2)			ln ADV (*t*-2)		
	ln OE (*t*-2)			ln OE (*t*-2)			ln OE (*t*-2)			ln OE (*t*-2)		
	ln RD (*t*-2)			ln RD (*t*-2)			ln RD (*t*-2)			ln RD (*t*-2)		
	OPM (*t*-2)			OPM (*t*-2)			OPM (*t*-2)			OPM (*t*-2)		
	EARN (*t*-2			EARN (*t*-2			EARN (*t*-2			EARN (*t*-2		
	CONC (*t*-2)			CONC (*t*-2)						CONC (*t*-2)		
	SIZE (*t*-2)			SIZE (*t*-2)						SIZE (*t*-2)		
	$\chi^2(6) = 6.16$, p =.41			$\chi^2(6) = 4.05$, p =.67			$\chi^2(4) = 3.13$, p =.54			$\chi^2(6) = 3.46$, p =.75		
Strength of outside instruments												
1st stage regression results	R^2	F-value	p-value	R^2	F-value	p-value	R^2	F-value	p-value	R^2	F-value	p-value
	.102	13.83	.00	.091	12.01	.00	.125	13.27	.00	.111	1012	.00

Appendix C: Corporate Valuation Model

Deriving Equation 2

In deriving our corporate valuation formula, we closely follow Copeland, Weston, and Shastri (2013, 497ff). Consistent with DCF valuation, the value of a company derives from its expected future cash flows that are discounted at the company's weighted average cost of capital (see also Equation 1 in the paper)[17]

$$FV_0 = \frac{EBIT_1 \times (1-\tau) - I_1}{(1+WACC)} + \frac{EBIT_2 \times (1-\tau) - I_2}{(1+WACC)^2} + \frac{EBIT_3 \times (1-\tau) - I_3}{(1+WACC)^3} + \ldots \tag{C.1}$$

The stream of cash flows can also be expressed as follows

$$\begin{aligned} FV_0 &= \frac{EBIT_1 \times (1-\tau) - I_1}{(1+WACC)} + \frac{EBIT_1 \times (1-\tau) + ROIC_1 \times I_1 - I_2}{(1+WACC)^2} \\ &+ \ldots + \frac{EBIT_1 \times (1-\tau) + \sum_{t=1}^{N-1} ROIC_t \times I_t - I_N}{(1+WACC)^N} \end{aligned} \tag{C.2}$$

where $ROIC_t \times I_t$ measures the net cash flows, which are assumed to cover the payments to suppliers of capital and the initial investment. Hence, cash flows from each year’s investment are sufficient to provide for the necessary replacement investment in the future.

Ignoring the unreasonable result that a firm has an infinite value, Copeland, Weston, and Shastri (2013, 499f) show that the sum in (C.2) has a solution that decomposes firm value into the value of current earnings strength and the value of future growth

$$FV_0 = \underbrace{\frac{EBIT_1 \times \left(1-\tau\right)}{WACC}}_{\substack{\text{Value of current} \\ \text{earnings strength}}} \times \underbrace{\left[1 + \frac{\left(ROIC - WACC\right) \times EGR \times S}{ROIC \times \left(1+WACC\right)}\right]}_{\text{Value of growth expectations}} \tag{C.3}$$

Note that the firm only generates value from future growth if this growth is profitable, i.e. the average rate of return of new invested capital ROIC is greater than the cost of capital

[17] Without loss of generality, we neglect the value contribution of a tax advantage that accrues from debt capital valued at market rates, which is not relevant for our derivation (Copeland, Weston, and Shastri (2013, 505).

WACC. It is not consistent with competition theory to assume that a firm can earn superior rents forever. Competition will eventually drive down ROIC to the level of WACC. Let the period of excess return denote with S. Let us further assume that the firm invests a constant fraction K of its cash flow into new investments, i.e. I_t = K×[EBIT (1- τ)]. Under the assumption of a limited period of excess returns, expression (C.3) can be restated as follows (Copeland, Weston, and Shastri, 502ff)

$$FV_0 = \frac{EBIT_t(1-\tau)}{WACC}\left[1+\frac{K\times\left(ROIC-WACC\right)}{1+ROIC\times K}\sum_{t=1}^{S}\left(\frac{1+ROIC\times K}{1+WACC}\right)^t\right] \tag{C.4}$$

which they further simplify to

$$FV_0 = \frac{EBIT_t(1-\tau)}{WACC}\left[1+\frac{K\times\left(ROIC-WACC\right)}{WACC-ROIC\times K}\left[1-\left(\frac{1+ROIC\times K}{1+WACC}\right)^S\right]\right] \tag{C.5}$$

Using the binomial expansion to approximate

$$\left(\frac{1+ROIC\times K}{1+WACC}\right)^S \cong 1-S\left(\frac{WACC-K\times ROIC}{1+WACC}\right) \quad , \tag{C.6}$$

substituting (C6) into (C5) and rearranging terms leads to

$$FV_0 = \frac{EBIT_t(1-\tau)}{WACC}+\frac{EBIT_t(1-\tau)\times K\times(ROIC-WACC)\times S}{WACC\times(1+WACC)} \tag{C.7}$$

Copeland, Weston, and Shastri (2013) prove that the following identity must hold

$$ROIC\times K = EGR\ , \tag{C.8}$$

where EGR measures the growth rate in earnings or cash flows, respectively. Substituting K for (C.8) in (C.7) and rearranging terms leads to our valuation formula (2) in the paper

$$FV_0 = \frac{EBIT_t(1-\tau)}{WACC} \times \left[1 + \frac{EGR \times (ROIC - WACC) \times S}{ROIC \times (1+WACC)} \right]. \tag{C.9}$$

Deriving Equation 8

We use expression (C.9) to obtain our measure of the sustainability of excess return (Equation 8 in the paper). Let us first bring EBIT(1-τ)/WACC on the left side of (C.9)

$$FV_0 - \frac{EBIT_t(1-\tau)}{WACC} = \frac{EBIT_t(1-\tau) \times EGR \times (ROIC - WACC) \times S}{ROIC \times WACC \times (1+WACC)} . \tag{C.10}$$

It is now straightforward to solve for S

$$S = \left(FV_0 - \frac{EBIT_t(1-\tau)}{WACC} \right) \left(\frac{ROIC \times WACC \times (1+WACC)}{EBIT_t(1-\tau) \times EGR \times (ROIC - WACC)} \right). \tag{C.11}$$

Since S is defined for ROIC > WACC and takes on only nonnegative values we obtain the following expression, which is consistent with Equation 8 in the paper

$$\tilde{S}_{it} = \left\{ \begin{array}{l} Max\left[\left(FV_0 - \frac{EBIT_t(1-\tau)}{WACC} \right) \left(\frac{ROIC \times WACC \times (1+WACC)}{EBIT_t(1-\tau) \times EGR \times (ROIC - WACC)} \right), 0 \right] \\ \text{for } \widetilde{ROIC}_{it} - \widetilde{WACC}_{it} > 0 \\ \qquad\qquad\qquad\qquad 0 \text{ else} \end{array} \right\}, \tag{C.12}$$

and where we use expected values for the value drivers.

Appendix D: Calculation of Elasticities

Value driver elasticities

First, consider a linear model of the form

$$y = a + bx + e\,, \tag{D.1}$$

where *y* is an outcome variable (e.g. *ROIC*), *x* is a predictor variable (e.g., *CBBE*), and *a*, *b*, and *e* are impact parameters that are usually to be estimated. The short-term elasticity $\varepsilon^{ST}{}_{y,x}$ is given by

$$\varepsilon^{ST}_{y,x} = b\frac{\mu_x}{\mu_y}\,, \tag{D.2}$$

where μ denotes the sample mean of the variable. We apply the specification (D.2) to compute the elasticities for the relations: *CBBE* $\rightarrow$ *ROIC, CBBE* $\rightarrow$ *EGR, CBBE* $\rightarrow$ *WACC.*

Second, with respect to the effect of advertising expenditures on *CBBE* our calculation is based on a linear-log relationship

$$y = a + b\ln x + e\,, \tag{D.3}$$

with the corresponding short-term elasticity

$$\varepsilon^{ST}_{y,x} = \frac{b}{\mu_y}\,, \tag{D.4}$$

Equations D.2 and D.4 measure the short-term elasticity. In a dynamic setting the long-term elasticities may be obtained by considering the carryover parameter λ as follows

$$\varepsilon^{LT} = \frac{\varepsilon^{ST}}{1-\lambda}\,, \tag{D.5}$$

In order to estimate the effect of CBBE on the level of earnings we follow the simulation approach by Edeling and Fischer (2016). They show that in models with a return variable as dependent and a level as independent variable

$$R_t = \frac{Y_t - Y_{t-1}}{Y_{t1}} = bx_t\,, \tag{D.6}$$

the level elasticity can be derived by simulation and yields

$$\varepsilon_{y,x}^{ST} = \frac{b}{1+\mu_R}\mu_x, \tag{D.7}$$

Finally, we compute the elasticity for *S*, the duration variable of Equation 7, as follows

$$\varepsilon_{y,x}^{LT} = \frac{1}{p}\delta_1\mu_x, \tag{D.8}$$

Note that by definition we cannot separate short- and long-term effects in duration models.

Firm value elasticities

We theoretically derive the firm value elasticities with respect to our value drivers using our firm value equation

$$FV_0 = \frac{EBIT_t(1-\tau)}{WACC} \times \left[1 + \frac{EGR \times (ROIC - WACC) \times S}{ROIC \times (1+WACC)}\right] \tag{D.9}$$

The elasticity of firm value with respect to one specific value driver *x* is defined as

$$\varepsilon_{FV,x} = \frac{\Delta FV / FV}{\Delta x / x} = \frac{\Delta FV}{\Delta x}\frac{x}{FV}, \tag{D.10}$$

Table D1 summarizes the theoretical firm value elasticities for the respective value driver and Table D2 presents information on the distribution of the firm-specific firm value elasticity estimations based on the firms from our study sample. Table D3 shows estimated advertising elasticities across industries. Please note that for advertising group sizes are too small to provide reasonable results with respect to disaggregate industries such as in Table D4. Table D4 provides details on individual industry means with respect to the estimated effects of CBBE on the value drivers and firm value.

Table D1
FIRM VALUE ELASTICITIES WITH RESPECT TO VALUE DRIVERS

Value driver	***Firm value elasticity***
Current earnings (*EBIT)*	$\varepsilon_{FV,Earnings} = 1$
Profitability (*ROIC*)	$\varepsilon_{FV,ROIC} = \dfrac{EBIT(1-\tau)\times EGR\times S}{ROIC\times FV\times\left(1+WACC\right)}$
Earnings growth (*EGR*)	$\varepsilon_{FV,EGR} = \dfrac{EBIT(1-\tau)}{WACC}\times\dfrac{(ROIC-WACC)\times S}{ROIC\times\left(1+WACC\right)}\times\dfrac{EGR}{FV}$
Cost of capital (*WACC*)	$\varepsilon_{FV,WACC} = \dfrac{EBIT(1-\tau)\times\left[(EGR\times S-ROIC)\times WACC^{2}-2ROIC\times WACC\times(EGR\times S+1)-EGR\times S\times ROIC-ROIC)\right]}{WACC^{2}\times\left(1+WACC\right)^{2}\times FV}$
Sustainability of excess returns (*S*)	$\varepsilon_{FV,x} = \dfrac{EBIT(1-\tau)}{WACC}\times\dfrac{(ROIC-WACC)\times EGR}{ROIC\times\left(1+WACC\right)}\times\dfrac{S}{FV}$

Table D2
VALUE DRIVER EFFECTS ON FIRM VALUE (DISTRIBUTION BASED ON FIRM-SPECIFIC ELASTICITIES)

	Elasticity estimates					
	Mean		*Median*	*# Firms*	*Positive effects (%)*	*Negative effects (%)*
Current earnings (*EBIT*)	1.000	***	1.000	613	100	0
Profitability (*ROIC*)	.390	***	.180	126	97	3
Earnings growth (*EGR*)	.373	***	.353	126	95	5
Cost of capital (*WACC*)	-4.426	***	-3.827	126	4	96
Sustainability of excess returns (*S*)	.373	***	.353	126	95	5

Notes: *** $p < .01$; ** $p < .05$

Table D3

ELASTICITIES OF VALUE DRIVERS AND FIRM VALUE WITH RESPECT TO ADVERTISING BY INDUSTRY

		Long-term advertising effect on firm value mediated by value drivers										*Total long-term advertising effect on firm value mediated by CBBE*	
		ADV → CBBE → EBIT[2)]		ADV → CBBE→ ROIC		ADV → CBBE→ EGR		ADV → CBBE→WACC		ADV → CBBE→ S			
Industry	Company brand examples	# firms	Marginal mean	# firms	Marginal mean	# firms	Marginal mean	# firms	Marginal mean	# firms	Marginal mean	# firms	Marginal mean
Consumer Discretionary	GM, Nike, Sony, Hilton, Saks	91	.001	49	$2.2x10^{-4}$	48	.014	50	-.010	49	.009	49	.025
Consumer Staples	Safeway, Walmart, Coca-Cola, Gillette	44	$-9.3x10^{-5}$	31	$3.3x10^{-4}$	30	$-2.7x10^{-4}$	31	.021	31	.007	29	.008
IT & Telecommunications	Google, HP, AT&T, Verizon	39	.001	20	$3.5x10^{-4}$	20	$-2.6x10^{-4}$	21	-.006	21	.004	19	.006
Industrials & Others[1)]	Ashland, BP	22	.002	13	$5.9x10^{-4}$	12	.030	13	-.002	13	.010	13	.034
Grand mean		227	.001***	121	$3.3x10^{-4}$***	117	.005***	123	.001***	122	.006***	117	.012***
F-value			5.29***		.503		7.43***		3.48***		3.54***		7.25***

[1)] Includes brands from GICS categories Transportation, Materials, Energy, and Utility.
[2)] CBBE effect on current earnings strength (EBIT) is a short-term effect per definition.
[3)] We do not report values for Health Care and Financial Services since the number of elasticity estimates is too small to infer substantial conclusions (N ≤ 8 for WACC, S, and firm value elasticities). We report a more detailed split including all industries in the Appendix.
Notes: *** $p < .01$; ** $p < .05$; EBIT = current earnings strength, ROIC = profitability, EGR = earnings growth forecasts, WACC = cost of capital, S = sustainability of excess returns.

Table D4
ELASTICITIES OF VALUE DRIVERS AND FIRM VALUE WITH RESPECT TO CBBE BY SINGLE INDUSTRY

		Long-term CBBE effect on firm value mediated by value drivers										*Total long-term CBBE effect on firm value*	
		CBBE→ EBIT[2)]		CBBE→ ROIC		CBBE→ EGR		CBBE→WACC		CBBE→ S			
Industry	Company brand examples	#Firms	Marginal mean	#Firms	Marginal mean	#Firms	Marginal mean	#Firms	Marginal mean	#Firms	Marginal mean	#Firms	Marginal mean
Consumer Discretionary		91	.090	48	.033	48	1.367	50	-.955	49	.620	49	2.254
Automobiles & Components	GM, Goodyear	8	.011	3	.058	3	.595	3	.170	3	.671	3	1.742
Consumer Durables & Apparel	Nike, Sony	19	.066	11	.022	11	1.017	11	-.361	11	.668	11	1.455
Consumer Services	Hilton, McDonald's	21	.120	9	.036	11	1.454	11	.570	11	.614	11	1.793
Media	CBS, Walt Disney	8	.071	3	.041	3	-.516	3	-.883	3	.474	3	.011
Retailing	Amazon, Saks	35	.108	22	.032	20	1.909	22	-2.176	21	.611	21	3.307
Consumer Staples		47	-.006	33	.040	32	.040	33	1.597	33	.446	32	.448
Food & Staples Retailing	Safeway, Walmart	10	.095	7	.079	7	1.620	7	1.073	7	.499	7	2.381
Food, Beverage & Tobacco	Hershey's, Coca Cola	26	-.008	21	.026	20	.080	21	1.959	21	.375	20	.347
Household & Personal Products	Gillette, Colgate-Palmolive	11	-.093	5	.040	5	-2.330	5	.811	5	.674	5	-1.854
Health Care	GlaxoSmithKline, Novartis	8	-.149	8	.022	7	-1.258	8	-.030	8	.253	7	-1.008
Financial services	Bank of America, MetLife	23	.082	0	-[3)]	0	-[3)]	0	-[3)]	0	-[3)]	0	-[3)]
Information Technology	Google, HP	33	.055	15	.025	15	.287	16	-.836	16	.299	14	.740
Telecommunication Services	AT&T, Verizon	7	.265	6	.020	6	1.440	6	-.471	6	.134	6	2.144
Transportation	Delta Airlines, Hertz	11	.190	7	.006	6	3.658	7	1.388	7	.851	7	3.986
Industrials & Others[1)]	Ashland, BP	11	.153	6	.088	6	2.785	6	-1.189	6	.552	6	3.679
Grand mean		231	.069***	123	.038***	120	.826***	126	.002	125	.513***	121	1.44***
F-value			3.25***		.446		3.84***		2.23**		2.63***		4.89***

[1)] Includes brands from GICS categories Materials, Energy, and Utility.
[2)] CBBE effect on current earnings strength (EBIT) is a short-term effect per definition.
[3)] Due to missing information on the liquidity measures in COMPUSTAT, we could not compute firm value effects for firms included in the financials industry sector.
Notes: *** p < .01; ** p < .05; EBIT = current earnings strength, ROIC = profitability, EGR = earnings growth forecasts, WACC = cost of capital, S = sustainability of excess returns.

Appendix E: Description of Customer-based Brand Equity (CBBE) Measure

Harris Interactive provided the customer-based brand equity metric from their EquiTrend brand-equity database. The EquiTrend brand equity score is a consumer survey measure that has been collected annually since 1989 for a representative selection of brands in the U.S. market. The company conducts annual online surveys of more than 20,000 U.S. consumers aged 15 and older that are representative of the entire population, and it calculates brand equity scores for more than 1,000 brands. Each respondent is asked to rate a total of 40 randomly selected brands. Each brand receives approximately 1,000 ratings. CBBE is measured by data on perceived quality, which is the primary component of a brand’s image, and familiarity, which corresponds to brand awareness. A brand's equity score is determined by first combining familiarity, quality, and purchase intent ratings at the individual respondent level. Familiarity is assessed by consumer ratings of familiarity with the brand on a 5-point scale (1 = “never heard of the brand,” 2 = “just know of the brand,” 3 = “somewhat familiar with the brand,” 4 = “very familiar with the brand,” and 5 = “extremely familiar with the brand”). Perceived quality is assessed by consumer ratings of the quality of the brand on an 11-point scale (0 = “unacceptable/poor,” 5 = “quite acceptable,” and 10 = “outstanding/extraordinary”). Purchase consideration is assessed by consumers’ ratings of intentions regarding their future relationship with the brand on an 11-point scale (0 = “never would purchase the brand,” and 10 = “absolutely would purchase the brand”). Finally, distinctiveness is assessed by consumer ratings of the differentiation of the brand on an 11-point scale (0 = “not distinctive at all,” and 10 = “totally distinctive from others”). The brand's total equity score is then aggregated across all respondents with some familiarity with the brand, and the result is indexed on a scale from 0 to 10. The top scores are publicly announced.

Appendix F: Support from Prior Literatures from Control Variables

Table F1
CONTROL VARIABLES AND EXPECTED IMPACT IN THE ESTIMATION EQUATIONS

	Profitability (Eq. 4)		***Analyst earnings growth forecast (Eq. 5)***		***Cost of capital (Eq. 6)***		***Sustainability (Eq. 7)***	
Variables	*Expected sign*	*Support*	*Expected sign*	*Support*	*Expected sign*	*Support*	*Expected sign*	*Support*
Advertising and other expenditures	+	Ailawadi et al. (2003); Rao, Bharadwaj (2008)	+	Kim, McAlister (2011); Joshi, Hanssens (2010)			+	Srivastava, et al. (1998); Vorhies, Morgan (2009)
R&D expenditures	+/-	Bouldin, et al. (1995); Erickson, Jacobson (1992)	+/-	Geroski et al. (1997); Erickson, Jacobson (1992)			+/-	MacDonald, Ryall (2004), Rappaport, Mauboussin (2001)
Firm size	-	McAfee, McMillan (1995)	-	Chan et al. (2003), McAfee, McMillan (1995)	-	Beaver, et al. (1970); Blume, et al. (1998)	+/-	Acs, Audretsch (1987); McAfee, McMillan (1995)
Industry concentration	+/-	Demsetz (1982); Scherer (1980)	+/-	Demsetz (1982); Scherer (1980)	+/-	Hou, Robinson (2006); Himme, Fischer (2014)	+/-	Demsetz (1982); Lustgarten, Thomadakis (1987)
Financial leverage	+	Kemsley, Nissim (2002)	-	Myers (1977)	-	Beaver, et al. (1970); Rego, et al. (2009)		
Previous earnings			+	Hou, Robinson (2006)				
Negative earnings dummy			+/-	Stickel (1990); Matsumoto (2002)				
Profitability			+	Copeland et al. (2013); Myers (1977)				
Investment rate			+	Copeland et al. (2013); Myers (1977)				
Pretax interest coverage					-	Blume, et al. (1998)		
Operating margin					-	Blume, et al. (1998)		
Dividend payout					-	Beaver, Kettler, Scholes (1970); Himme, Fischer (2014)		
Asset Growth					+	Beaver, et al. (1970)		
Liquidity					-	Beaver, et al. (1970)		

Appendix G: Sobel Mediation Test

In Table G1, we report on the Sobel test, which formally tests whether our mediation assumption with respect to CBBE and the four value drivers holds (Sobel 1986). Except for WACC, we cannot reject this assumption. Moreover, we find support for a full mediation of the impact of CBBE on firm value via the value drivers since the direct effect of CBBE on firm value is not significant.

Table G1
TESTING THE MEDIATION OF CBBE ON FIRM VALUE BY VALUE DRIVER

	Effect of CBBE on value driver		*Effect of value driver on firm value*		*Sobel test*	
	Estimate	(Standard error)	Estimate	(Standard error)	Test statistic	p-value
Profitability	.001	($2.7x10^{-4}$)	29,149.1	4,624.54	2.39	.02
Earnings growth	.003	(.001)	3,548.6	1,433.20	1.93	.03
Cost of capital	$1.1x10^{-4}$	($9.8x10^{-5}$)	-199,298.0	31,997.98	-1.11	.87
Sustainability of excess returns	.011	(.003)	174.4	37.45	2.69	.00

Appendix H: Robustness Checks

Distributional Assumptions of Sustainability of Excess Returns

We tested alternative distributions of the sustainability of excess returns in Equation 7. Specifically, we considered the following distributions: Weibull, inverse Gaussian, Gamma, loglogistic, lognormal, and Generalized F. Inspecting the integrated hazard function line (Greene 2012) and the Bayesian Information Criterion (BIC), we conclude that the Weibull distribution best represents the data (see Figure H1 below for details).

Omitted Variable Bias

We acknowledge that CBBE is certainly not the only relevant market-based asset that may impact the value drivers and ultimately firm value. If such variables are not controlled for they may severely bias our results. We effectively account for customer asset strength and other variables across firms by specifying a random intercept. In addition, we check for a potential variable omission bias by adding customer asset strength to our equations. Specifically, we adopt the customer asset strength measure suggested by Fang et al. (2011). Including this variable reduces the sample sizes dramatically by more than 30%. Estimation results are consistent with our main results. Most importantly, the size of the CBBE coefficients do not differ significantly from each other suggesting that our results are not subject to a variable omission bias (see Table H1).

Model Dynamics

We estimated several alternative dynamic specifications. We estimated a Koyck specification. This requires adding an autocorrelation term to the error although we find no evidence for serial correlation. We also estimated a model without the lagged dependent variable but with serially correlated errors. We compare these two alternative dynamic specifications with our proposed specification in terms of model fit (BIC and Pseudo R^2) and apply the Davidson/MacKinnon non-nested model specification test (Greene 2012). Based on these test statistics, none of the alternative specifications turns out to be superior to the suggested one. The size and significance of our focal estimates in the alternative specifications are also similar (see Table H2-H4).

Alternative Estimation Approaches

We also checked the stability of results when we apply alternative estimation approaches. First, we add industry dummies to control for trend heterogeneity across industries. These dummies turn out to be insignificant and are rejected by nested model tests ($p > .05$). Furthermore, we estimate our equations assuming CBBE to be exogenous, i.e. no instrumental variables are used (see Table H5). We then apply 3SLS to a dataset that needs to be balanced (see Table H6). 3SLS explicitly accounts for both error correlations across equations and endogeneity of CBBE. However, it does not allow for a random constant. Despite of these limitations we find much consistency with our estimation results.

Parameter Stability

We checked the stability of the CBBE parameter over time. Specifically, we compare estimates from the first half of years (2005-2009) with the second half (2010-2013). We do not detect any significant change (see Table H7).

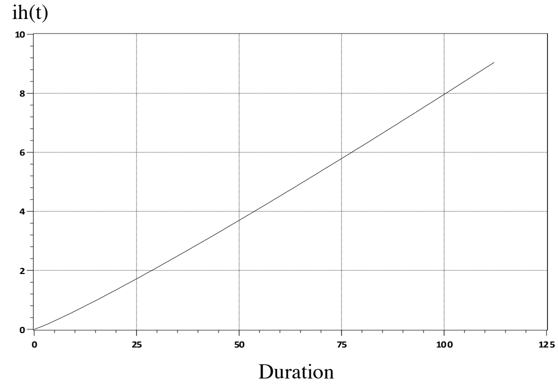
Sample Composition

Finally, we checked the sensitivity of our results to variations in sample composition. For this purpose, we constructed a balanced dataset that includes only identical firm-period observations across all equations. This procedure reduces sample size to 486 observations. We re-estimated our models with this dataset (see Table H8). The results are in line with our focal model results that are based on unbalanced, larger samples.

FIGURE H1
INTEGRATED HAZARD FUNCTION ih(t)=-logS(t) AND BIC FOR DIFFERENT DISTRIBUTION ASSUMPTIONS

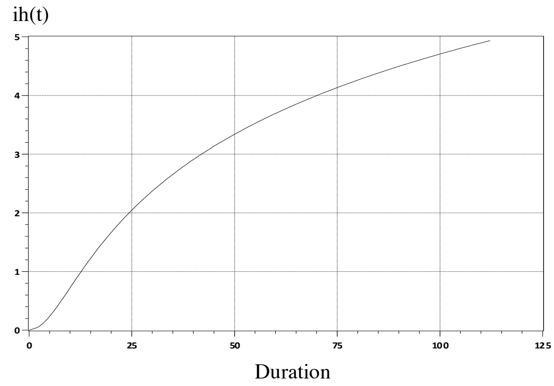
Weibull

BIC = 2.704



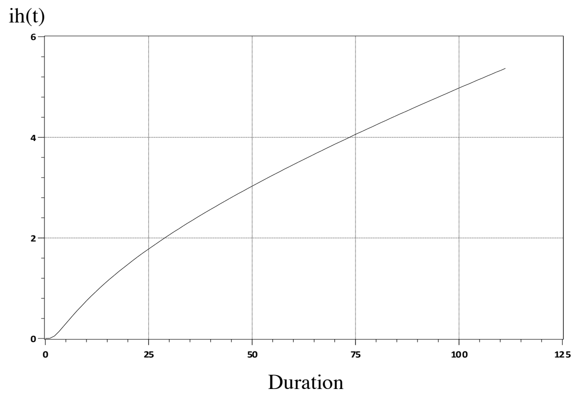
Loglogistic

BIC = 2.719



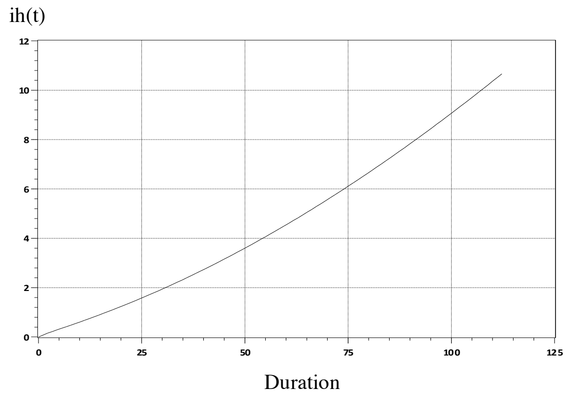
Inverse Gaussian

BIC = 7.427



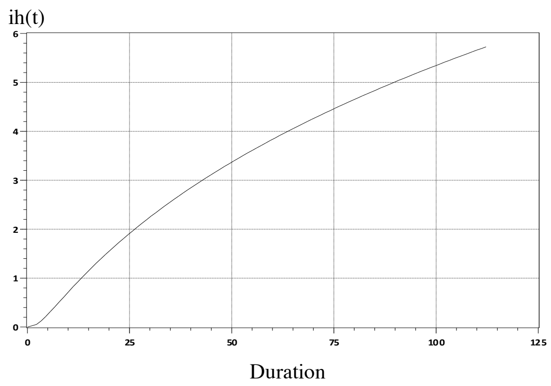
Gamma

BIC = 3.008



Lognormal

BIC = 2.726



Generalized F

BIC = 2.718

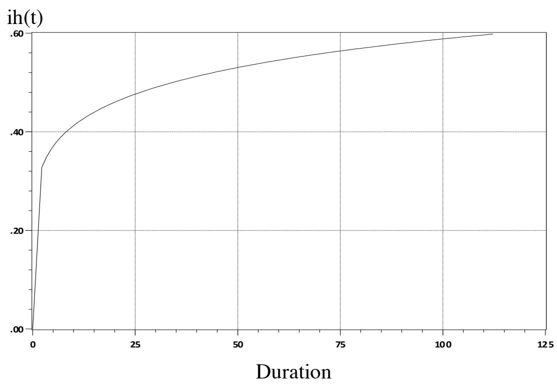


Table H1
IV ESTIMATION RESULTS INCLUDING CUSTOMER ASSET STRENGTH

	Profitability (Eq. 4)		*Analyst earnings growth forecast (Eq. 5)*		*Cost of capital (Eq. 6)*		*Sustainability of excess return (Eq. 7)*	
	Expected sign	Coefficient (Standard Error)	Expected sign	Coefficient (Standard Error)	Expecte d sign	Coefficient (Standard Error)	Expected sign	Coefficient (Standard Error)
Intercept		.269 (.044)***		-.032 (.033)		.136 (.009)***		.528 (.426)
Estimated SD		.503 (.032)***		.414 (.103)***		.033 (.007)***		1.13 (.237)***
Dependent variable (*t*-1)	+	.303 (.016)***	+	.769 (.025)***	+	.271 (.041)***		---
CBBE (*t*-1)	+	**.002 (.001)***	+	**.006 (.003)***	**+/-[1]**	**3.20 (2.70)**	+	**.012 (.004)*****
Estimated SD		**.003 (1.5x10^{-4})*****		**.001 (3.2x10^{-4})****	**[1]**	**.116 (.303)**		**.014 (.001)*****
Customer asset strength (*t*-1)	+	**.247 (.189)**	+	**1.00 (.482)****	+	**.064 (.041)**	+	**.656 (1.69)*****
Estimated SD		**.044 (.020)****		**.027 (.039)**		**.023 (.004)*****		**.918 (.095)*****
Advertising expenditures (*t*-1)[1]	+/-	.044 (.029)	+/-	.053 (.055)			+/-	.032 (.269)
R&D expenditures (*t*-1) [1]	+/-	.012 (.023)	+/-	.064 (.050)			+/-	-.296 (.194)
Other expenditures (*t* -1) [1]	+/-	.041 (.010)***	+/-	-.032 (.027)			+/-	-.446 (.076)***
Operating margin (*t* -1)					-	-.017 (.010)*		
Previous year's earnings [1]			+/-	-.026 (.026)				
Negative earnings dummy (*t*-1)			+	-.052 (.035)				
Financial leverage (*t*-1) [1]	+	.001 (.000)***	-	-1.70 (6.00)	+/-	-2.10 (.955)**		
Profitability (*t*-1)			+	.027 (.071)				
Investment rate (*t*-1) [1]			+	.082 (26.8)				
Pretax interest coverage (*t*-1) [1]					-	1.0x10^{-5} (.001)		
Dividend payout (*t*-1)[1]					+	1.30 (11.8)		
Asset growth (*t*-1)					-	.004 (.004)	+	.499 (.136)**
Liquidity (*t*-1) [1]					+	.857 (.001)		
US GDP growth (*t*-1)	+/-	-.007 (.272)	+/-	-.233 (.718)			+/-	7.57 (1.17)***
Negative earnings dummy (*t*-1)	+/-	-.012 (.004)***	-	.010 (.011)	-	-.004 (.001)***	+/-	.092 (.040)**
Financial leverage (*t*-1) [1]	+/-	-.007 (.272)	+/-	-.114 (.080)	+/-	-.029 (.007)***	+/-	.912 (.242)***
Sample size		755		571		476		262
BIC		-1,145.3		-420.9		-2,315.9		679.1
BIC (base specification see paper)		-2,007.3		-711.0		-3,219.8		1013.7
Difference test for CBBE	t-value	p-value	t-value	p-value	t-value	p-value	t-value	p-value
parameter estimates	1.04	.23	.95	.26	.73	.31	.24	.39

Notes: Two-sided t-tests. e *** p < .01; ** p < .05; * p < .1.
[1] For reading convenience, coefficients are multiplied by 10,000.

Table H2
OVERVIEW OF FIT STATISTICS AND J-TEST RESULTS FOR ALTERNATIVE DYNAMIC SPECIFICATIONS

	CBEE (Eq. 3)	*Profitability (Eq. 4)*	*Analyst earnings growth forecast (Eq. 5)*	*Cost of capital (Eq. 6)*
Current specification (see the paper)	Pseudo R^2 = .91 BIC = 5908.18	Pseudo R^2 = .87 BIC = -2007.3	Pseudo R^2 = .67 BIC= -711.0	Pseudo R^2 = .65 BIC= -3219.8
Current specification with autocorrelation (Koyck specification)	Pseudo R^2 = .89 BIC = 5908.24 J-Test: no decision Very similar size/significance of focal coefficients	Pseudo R^2 = .77 BIC = -1530.2 J-Test: no decision Very similar size/significance of focal coefficients	Pseudo R^2 = .51 BIC = -349.3 J-Test: no decision Similar size/significance of focal coefficients	Pseudo R^2 = .63 BIC = -2409.4 J-Test: no decision Similar size/significance of focal coefficients
Autocorrelated error and no lagged dependent variable	Pseudo R^2 = .88 BIC = 6421.06 J-Test: no decision Similar size/significance of focal coefficients	Pseudo R^2 = .77 BIC = -1482.36 J-Test: no decision Very similar size/significance of focal coefficients	Pseudo R^2 = .33 BIC = -255.94 J-Test: model rejected Very similar size/significance of focal coefficients	Pseudo R^2 = .61 BIC = -2390.1 J-Test: no decision Similar size/significance of focal coefficients:

Table H3

ESTIMATION RESULTS FOR ALTERNATIVE DYNAMIC SPECIFICATIONS – AUTOCORRELATED ERROR STRUCTURE (KOYCK SPECIFICATION)

	CBEE (Eq. 3)		*Profitability (Eq. 4)*		*Analyst earnings growth forecast (Eq. 5)*		*Cost of capital (Eq. 6)*	
	Expected sign	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*
Intercept		53.74 (1.30)***		.393 (.023)***		.143 (.002)***		.127 (.008)***
Estimated SD		3.15 (.086)***		.011 (.018)***		.418 (.002)***		.022 (.006)***
Carryover								
Dependent variable (*t*-1)	+	.319 (.023)***	+	.258 (.014)***	+	.998 (.001)***	+ [1]	.212 (.036)***
Marketing constructs								
CBBE (*t*-1)		---	+	.001 (3.0x10^{-4})***	+	.002 (2.0x10^{-5})***	+/- [1]	-1.08 (1.10)
Estimated SD		---		.001 (3.7x10^{-5})***		.005 (7.2x10^{-6})***	[1]	2.01 (.122)***
Advertising expenditures (*t*-1)	+[2]	.464 (.072)***	+/-[1]	.016 (.019)	+/-[1]	.199 (.001)***		---
Estimated SD		.500 (.005)***		---		---		---
Controls								
R&D expenditures (*t*-1)	+/-[2]	-.071 (.008)***	+/-[1]	-.041 (.013)***	+/-[1]	-.027 (.001)***		---
Other expenditures (*t*-1)	+[2]	.011 (.010)	+/-[1]	.013 (.003)**	+/- [1]	3.2x10^{-4} (2.7x10^{-4})		---
Operating margin (*t*-1)	+	1.65 (.403)***		---		---	-	-.032 (.009)***
Earnings (*t*-1) [1]	+	1.52 (.158)***		---	+/-	-.002 (2.8x10^{-4})**		---
Negative earnings dummy (*t*-1)		---		---	+	.001 (.001)		---
Financial leverage (*t*-1)		---	+	.001 (1.0x10^{-4})***	+/- [1]	-.235 (.008)	+/- [1]	-.528 (.643)
Profitability (*t*-1)		---		---	+	.001 (.001)		---
Investment rate (*t*-1) [1]		---		---	+	-.079 (.722)		---
Pretax interest coverage (*t*-1) [1]		---		---		---	---	.001 (.002)
Dividend payout (*t*-1)[1]		---		---		---	+	-1.11 (11.4)
Asset growth (*t*-1)		---		---		---	-	.005 (.004)
Liquidity (*t*-1) [1]		---		---		---	+	.001 (.001)
US GDP growth (*t*-1)		---	+/-	.023 (.113)	+/-	-.030 (.007)		---
Observed firm & market heterogeneity								
Firm size (*t*-1)	+/-	-.366 (.063)***	+/-	-.018 (.002)***		.005 (1.3x10^{-4})	-	-.002 (.001)***
Industry concentration (*t*-1)	+/-	-2.43 (.684)***	+/-	-.191 (.019)***	+/-	.015 (.001)***	+/-	-.034 (.006)***
Sample size		1033		845		751		486
Pseudo R^2		.898		.777		.512		.630

Notes: Two-sided t-tests. Pseudo R^2 measures the squared correlation between actual and predicted values of the dependent variable *** $p < .01$; ** $p < .05$; * $p < .1$. [1] For reading convenience, coefficients are multiplied by 10,000. [2] Log values.

Table H4

ESTIMATION RESULTS FOR ALTERNATIVE DYNAMIC SPECIFICATIONS – AUTOCORRELATED ERROR AND NO LAGGED DEPENDENT VARIABLE

	CBEE (Eq. 3)		*Profitability (Eq. 4)*		*Analyst earnings growth forecast (Eq. 5)*		*Cost of capital (Eq. 6)*	
	Expected sign	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*
Intercept		49.94 (1.31)***		.441 (.023)***		-.099 (.125)***		.123 (.008)***
Estimated SD		9.80 (1.23)***		.092 (.018)***		.734 (.094)***		.028 (.007)***
Carryover								
Dependent variable (*t*-1)		---		---		---		---
Marketing constructs								
CBBE (*t*-1)		---	+	.001 ($3.1x10^{-4}$)***	+	.004 (.001)***	+/-[1]	.002 (1.10)
Estimated SD		---		.001 ($3.8x10^{-5}$)***		.001 ($1.4x10^{-4}$)***	[1]	.562 (.117)***
Advertising expenditures (*t*-1)	+[2]	.568 (.073)***	+/-[1]	.047 (.002)**	+/-[1]	.233 (.068)***		---
Estimated SD		.218 (.004)***		---		---		---
Controls								
R&D expenditures (*t*-1)	+/-[2]	-.016 (.008)*	+/-[1]	-.065 (.013)***	+/-[1]	.228 (.055)***		---
Other expenditures (*t*-1)	+[2]	-.048 (.010)***	+/-[1]	.012 (.003)***	+/-[1]	-.006 (.016)		---
Operating margin (*t*-1)	+	1.03 (.328)***		---		---	-	-.033 (.009)***
Earnings (*t*-1)[1]	+	1.75 (.161)***		---	+/-	-.049 (.027)*		---
Negative earnings dummy (*t*-1)		---		---	+	-.065 (.061)***		---
Financial leverage (*t*-1)		---	+	.001 ($1.1x10^{-4}$)***	+/-[1]	-.912 (7.10)	+/-[1]	-1.10 (.688)*
Profitability (*t*-1)		---		---	+	.046 (.093)		---
Investment rate (*t*-1)[1]		---		---	+	-.475 (154.3)		---
Pretax interest coverage (*t*-1)[1]		---		---		---	-	.001 (.002)
Dividend payout (*t*-1)[1]		---		---		---	+	-2.87 (12.5)
Asset growth (*t*-1)		---		---		---	-	.007 (.004)*
Liquidity (*t*-1)[1]		---		---		---	+	2.02 (7.50)
US GDP growth (*t*-1)		---	+/-	.113 (.108)	+/-	.111 (.753)		---
Observed firm & market heterogeneity								
Firm size (*t*-1)	+/-	-.077 (.062)	+/-	-.022 (.002)***	-	-.122 (.104)	-	-.002 (.001)***
Industry concentration (*t*-1)	+/-	-3.78 (.684)***	+/-	-.207 (.019)***	+/-	-.069 (.112)	+/-	-.034 (.006)***
Sample size		1111		815		751		486
Pseudo R^2		.884		.779		.325		.613

Notes: Two-sided t-tests. Pseudo R^2 measures the squared correlation between actual and predicted values of the dependent variable *** $p < .01$; ** $p < .05$; * $p < .1$. [1] For reading convenience, coefficients are multiplied by 10,000. [2] Log values.

Table H5
ESTIMATION RESULTS WITHOUT INSTRUMENTAL VARIABLES (1/2)

	Profitability (Eq. 4)		*Analyst earnings growth forecast (Eq. 5)*		*Cost of capital (Eq. 6)*	
	Expected sign	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*
Intercept		.305 (.022)***		.051 (.070)		.121 (.005)***
Estimated SD		6.7 x 10^{-5} (.142)		.308 (.046)***		.006 (.004)*
Carryover						
Dependent variable (*t*-1)	+	.426 (.008)***	+	.714 (.016)***	+ [1)]	.259 (.026)***
Marketing constructs						
CBBE (*t*-1)	+	.001 (2.6 x 10^{-4})***	+	.002 (.001)**	+/- [1)]	.370 (.594)
Estimated SD		.011 (1.5 x 10^{-4})***		.001 (8.5 x 10^{-5})***		.670 (.078)***
Advertising expenditures (*t*-1)	+/-[1)]	.041 (.020)**	+/-[1)]	.285 (.038)***		---
Controls						
R&D expenditures (*t*-1)	+/-[1)]	-.109 (.017)***	+/-[1)]	.177 (.031)***		---
Other expenditures (*t*-1)	+/-[1)]	-.020 (.004)***	+/- [1)]	.002 (.009)		---
Operating margin (*t*-1)		---		---	-	-.001 (.003)
Earnings (*t*-1) [1)]		---	+/-	-.049 (.014)***		---
Negative earnings dummy (*t*-1)		---	+	.022 (.020)		---
Financial leverage (*t*-1) [1)]	+	3.60 (.687)	+/-	-1.59 (5.70)	+/-	.049 (.473)
Profitability (*t*-1)		---	+	.003 (.023)		---
Investment rate (*t*-1) [1)]		---	+	-.564 (19.0)		---
Pretax interest coverage (*t*-1) [1)]		---		---	-	.001 (.002)
Dividend payout (*t*-1)[1)]		---		---	+	-.001 (.001)
Asset growth (*t*-1)		---		---	-	.003 (.002)
Liquidity (*t*-1) [1)]		---		---	+	3.69 (5.00)
US GDP growth (*t*-1)	+/-	.096 (.106)	+/-	-.089 (.361)		---
Observed firm & market heterogeneity						
Firm size (*t*-1)	+/-	-.015 (.002)***	-	-.001 (.005)***	-	-.003 (3.4 x 10^{-4})***
Industry concentration (*t*-1)	+/-	.043 (.018)***	+/-	-.082 (.053)***	+/-	-.017 (.003)***
Sample size		1,317		1,162		1,125
Pseudo R^2		.793		.483		.606

Notes: Two-sided t-tests. Pseudo R^2 measures the squared correlation between actual and predicted values of the dependent variable *** p < .01; ** p < .05; * p < .1. [1)] For reading convenience, coefficients are multiplied by 10,000.

Table H5

ESTIMATION RESULTS WITHOUT INSTRUMENTAL VARIABLES (2/2)

	Expected sign	*Expected sustainability of excess return (Eq. 7)* Coefficient (Standard Error)
Intercept		1.01 (.265)***
Estimated SD		3.41 (.202)***
Marketing constructs		
CBBE (*t*-1)	+	.010 (.003)***
Estimated SD		.013 ($4.0x10^{-4}$)***
Advertising expenditures (*t*-1) [1)]	+/-	-.187 (.212)
Controls		
R&D expenditures (*t*-1) [1)]	+	-.675 (.140)***
Other expenditures (*t*-1) [1)]	+/-	-.228 (.027)***
Asset growth (*t*-1)	+	.127 (.024)***
US. GDP Growth	+/-	7.02 (.817)**
Observed firm & market heterogeneity		
Firm size (*t*-1)	+/-	.127 (.024)***
Industry concentration (*t*-1)	+/-	-.294 (.169)*
Weibull scale parameter 1/p		.425 (.013)***
Sample size		399
Log Likelihood		-441.4
Pseudo R²		.742

Notes: Two-sided t-tests. *** p < .01; ** p < .05; * p < .1 . [1)] For reading convenience, coefficients are multiplied by 10,000.

Table H6
3SLS ESTIMATION RESULTS (BALANCED SAMPLE) (1/2)

	CBEE (Eq. 3)		*Profitability (Eq. 4)*		*Analyst earnings growth forecast (Eq. 5)*		*Cost of capital (Eq. 6)*	
	Expected sign	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*
Intercept		53.06 (5.21)***		.345 (.156)***		-.488 (.192)***		.125 (.021)***
Carryover								
Dependent variable (*t*-1)	+	.124 (.137)	+	.464 (.096)***	+	.785 (.063)***	+	.129 (.069)*
Marketing constructs								
CBBE (*t*-1)		---	+	.004 (.002)*	+	.007 (.003)**	+/- [1)]	-1.29 (3.30)
Advertising expenditures (*t*-1)	+[2)]	.755 (.321)**	+/-[1)]	.040 (.063)	+/-[1)]	.210 (.079)***		---
Controls								
R&D expenditures (*t*-1)	+/-[2]	.059 (.036)	+/-[1)]	.109 (.045)*	+/-[1)]	.108 (.059)*		---
Other expenditures (*t*-1)	+[2)]	-.085 (.057)	+/-[1)]	.026 (.010)**	+/- [1)]	-.052 (.016)		---
Operating margin (*t*-1)	+	-20.02 (3.73)***		---		---	-	-.051 (.012)***
Earnings (*t*-1) [1)]	+	.451 (.727)		---	+/-	-.046 (.027)*		---
Negative earnings dummy (*t*-1)		---		---	+	-.085 (.059)		---
Financial leverage (*t*-1) [1)]		---	+	.001 (.001)	+/-[1)]	-1.44 (10.1)	+/-[1)]	-3.78 (1.00)***
Profitability (*t*-1)		---		---	+	-.035 (.051)		---
Investment rate (*t*-1) [1)]		---		---	+	.130 (.045)***		---
Pretax interest coverage (*t*-1) [1)]		---		---		---	-	.001 (3.8x10^{-4})***
Dividend payout (*t*-1)[1)]		---		---		---	+	-.002 (.002)
Asset growth (*t*-1)		---		---		---	-	.012 (.006)**
Liquidity (*t*-1) [1)]		---		---		---	+	.005 (.001)***
US GDP growth (*t*-1)		---	+/-	-.295 (.328)	+/-	.124 (.392)***		---
Observed firm & market heterogeneity								
Size (t-1)	+/-	-.094 (.438)	+/-	-.029 (.008)***	-[1)]	.008 (.011)	-	-.001 (.001)
Industry concentration (t-1)	+/-	-8.98 (2.74)***	+/-	-.053 (.067)	+/-	.028 (.087)	+/-	-.026 (.008)***
Sample size		486		486		486		486
R^2		.110		.071		.257		.202

Notes: Two-sided t-tests. Pseudo R^2 measures the squared correlation between actual and predicted values of the dependent variable *** $p < .01$; ** $p < .05$; * $p < .1$. [1)] For reading convenience, coefficients are multiplied by 10,000.

Table H6

3SLS ESTIMATION RESULTS (BALANCED SAMPLE) (2/2)

	Expected sustainability of excess return (Eq. 7)	
	Expected sign	*Coefficient (Standard Error)*
Intercept		1.26 (.944)
Estimated SD		14.32 (.675)***
Marketing constructs		
CBBE (*t*-1)	+	.029 (.015)**
Estimated SD		.010 (.001)***
Advertising expenditures (*t*-1) [1)]	+/-	-.339 (.255)
Controls		
R&D expenditures (*t*-1) [1)]	+	-.609 (.166)***
Other expenditures (*t*-1) [1)]	+/-	.034 (.033)
Asset growth (*t*-1)	+	.986 (.126)***
US. GDP Growth	+/-	.829 (1.29)
Observed firm & market heterogeneity		
Firm size (*t*-1)	+/-	-.108 (.030)***
Industry concentration (*t*-1)	+/-	1.15 (.252)***
Weibull scale parameter 1/p		.465 (.018)***
Sample size		298
Log Likelihood		-339.4
Pseudo R²		.715

Notes: Two-sided t-tests. *** $p < .01$; ** $p < .05$; * $p < .1$. [1)] For reading convenience, coefficients are multiplied by 10,000.

Table H7
TESTING CBBE PARAMETER STABILITY OVER TIME

	Profitability (Eq. 4)		*Analyst earnings growth forecast (Eq. 5)*		*Cost of capital (Eq. 6)*		*Expected sustainability of excess return (Eq. 7)*	
	Expected sign	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*
Intercept		.461 (.022)***		.003 (.083)		.129 (.009)***		.973 (.339)***
Estimated SD		.111 (.011)***		.515 (.061)***		.024 (.006)***		1.15 (.247)***
Carryover								
Dependent variable (*t*-1)	+	.331 (.008)***	+	.712 (.020)***	+	.282 (.036)***		---
Marketing constructs								
CBBE (*t*-1)	+	.001 (2.7×10^{-4})***	+	.003 (.001)***	+	.130 (1.30)	+	.973 (.339)***
Estimated SD		.003 (2.3×10^{-5})***		.001 (9.8×10^{-5})***		.650 (.105)***		1.15 (.247)***
Advertising expenditures (*t*-1)	+/-[1)]	.042 (.018)**	+/-[1)]	.303 (.044)***	+/-[1)]	---	+/-[1)]	.973 (.339)***
CBBE x Time		**-.413 (.830)**		**-.504 (4.30)**		**1.5×10^{-4} (2.4×10^{-4})**		**-.001 (.001)**
Controls								
R&D expenditures (*t*-1)	+/-[1)]	-.045 (.012)***	+/-[1)]	.177 (.010)***		---	+[1)]	-.250 (.164)
Other expenditures (*t*-1)	+/-[1)]	.012 (.003)***	+/-[1)]	.002 (.034)		---	+/-	-.188 (.031)***
Operating margin (*t*-1)		---		---	-	-.028 (.007)***		---
Earnings (*t*-1)[1)]		---	+/-	-.005 (.002)***		---		---
Negative earnings dummy (*t*-1)		---	+	.106 (.027)***		---		---
Financial leverage (*t*-1)[1)]	+	.160 (.072)***	-	-1.632 (5.60)	+/-	-.857 (.603)		---
Profitability (*t*-1)		---	+/-	.037 (.045)		---		---
Investment rate (*t*-1)[1)]		---	+	-.548 (24.4)		---		---
Pretax interest coverage (*t*-1)[1)]		---		---	-	.001 (.001)		---
Dividend payout (*t*-1)[1)]		---		---	+	1.10 (11.2)		---
Asset growth (*t*-1)		---		---	-	.005 (.003)	+	.456 (.139)***
Liquidity (*t*-1)[1)]		---		---	+	.001 (.001)		---
US GDP growth (*t*-1)	+/-	.071 (.105)	+/-	.065 (.095)		---	+/-	8.31 (.997)***
Observed firm & market heterogeneity								
Firm size (*t*-1)	+/-	-.025 (.001)***	+/-	2.100 (55.7)	+/-[1)]	-.003 (.001)***	+/-	.072 (.030)**
Industry concentration (*t*-1)	+/-	-.100 (.017)***	+/-	-.095 (.060)	+/-	-.026 (.006)***	+/-	.501 (.221)**
Sample size		1,084		979		649		347
Pseudo R^2		.847		.824		.700		.659

Notes: Two-sided t-tests. Pseudo R^2 measures the squared correlation between actual and predicted values of the dependent variable *** $p < .01$; ** $p < .05$; * $p < .1$. [1)] For reading convenience, coefficients are multiplied by 10,000.

Table H8

ESTIMATION RESULTS WITH BALANCED SAMPLE (=IDENTICAL FIRM-PERIOD OBSERVATIONS ACROSS EQUATIONS) (1/2)

	CBEE (Eq. 3)		*Profitability (Eq. 4)*		*Analyst earnings growth forecast (Eq. 5)*		*Cost of capital (Eq. 6)*	
	Expected sign	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*	*Expected sign*	*Coefficient (Standard Error)*
Intercept		44.82 (.174)***		.360 (.040)***		-.372 (.177)**		.100 (.010)***
Estimated SD		5.627 (.129)***		.068 (.025)***		.773 (.132)***		.011 (.008)***
Carryover								
Dependent variable (t-1)	+	.201 (.031)***	+	.225 (.034)***	+	.804 (.144)***	+[1]	.178 (.062)***
Marketing constructs								
CBBE (t-1)		---	+	.002 (2.5×10^{-4})***	+	.005 (.002)***	+/-[1]	2.18 (1.3)
Estimated SD		---		.004 (4.2×10^{-5})***		.001 (1.7×10^{-4})***	[1]	.836 (.128)***
Advertising expenditures (t-1)	+[2]	.214 (.109)**	+/-[1]	.047 (.022)**	+/-[1]	.342 (.073)***		---
Estimated SD		.404 (.007)***		---		---		---
Controls								
R&D expenditures (t-1)	+/-[2]	-.054 (.013)***	+/-[1]	-.109 (.017)***	+/-[1]	.075 (.065)		---
Other expenditures (t-1)	+[2]	.157 (.019)***	+/-[1]	-.008 (.004)**	+/-[1]	-.015 (.018)		---
Operating margin (t-1)	+	-2.44 (1.19)**		---		---	-	-.055 (.012)***
Earnings (t-1)[1]	+	.605 (.252)***		---	+/-	-.040 (.036)		---
Negative earnings dummy (t-1)		---		---	+	-.065 (.061)		---
Financial leverage (t-1)[1]		---	+	.001 (.001)	+/-	-5.03 (14.6)	+/-	-3.808 (1.0)***
Profitability (t-1)		---		---	+	-.044 (.081)		---
Investment rate (t-1)[1]		---		---	+	.141 (.057)**		---
Pretax interest coverage (t-1)[1]		---		---		---	-	.001 (.002)
Dividend payout (t-1)[1]		---		---		---	+	-.001 (.001)
Asset growth (t-1)		---		---		---	-	.003 (.005)
Liquidity (t-1)[1]		---		---		---	+	.003 (.002)***
US GDP growth (t-1)		---	+/-	.106 (.148)	+/-	.008 (.908)		---
Observer firm & market heterogeneity								
Firm size (t-1)	+/-	.903 (.147)***	+/-	-.006 (.003)*	-[1]	.016 (.015)	-	-.001 (.001)**
Industry concentration (t-1)	+/-	-4.14 (.962)***	+/-	-.429 (.022)***	+/-	-.069 (.112)	+/-	-.027 (.007)***
Sample size		486		486		486		486
Pseudo R^2		.915		.939		.577		.650

Notes: Two-sided t-tests. Pseudo R^2 measures the squared correlation between actual and predicted values of the dependent variable *** $p < .01$; ** $p < .05$; * $p < .1$. [1] For reading convenience, coefficients are multiplied by 10,000. [2] Log values.

Table H8

ESTIMATION RESULTS WITH BALANCED SAMPLE (=IDENTICAL FIRM-PERIOD OBSERVATIONS ACROSS EQUATIONS) (2/2)

	Expected sustainability of excess return (Eq. 7)	
	Expected sign	*Coefficient (Standard Error)*
Intercept		.533 (.421)
Estimated SD		2.31 (.336)***
Marketing constructs		
CBBE (*t*-1)	+	.012 (.004)***
Estimated SD		.013 (.001)***
Advertising expenditures (*t*-1) [1)]	+/-	-.140 (.260)
Controls		
R&D expenditures (*t*-1) [1)]	+	-.187 (.179)
Other expenditures (*t*-1) [1)]	+/-	-.204 (.032)***
Asset growth (*t*-1)	+	.456 (.139)***
US. GDP Growth	+/-	6.90 (1.40)***
Observed firm & market heterogeneity		
Firm size (*t*-1)	+/-	.130 (.035)***
Industry concentration (*t*-1)	+/-	-.185 (.220)
Weibull scale parameter 1/p		.468 (.016)***
Sample size		274
Log Likelihood		-321.0
Pseudo R^2		.556

Notes: Two-sided t-tests. *** $p < .01$; ** $p < .05$; * $p < .1$. [1)] For reading convenience, coefficients are multiplied by 10,000.

References Appendix Paper 3

Acs, Zoltan J. and David B. Audretsch (1987), “Innovation, Market Structure, and Firm Size,” *The Review of Economics and Statistics*, 69 (4), 567-574.

Ailawadi, Kusum L., Donald R. Lehmann, and Scott A. Neslin (2003), “Revenue Premium as an Outcome Measure of Brand Equity,” *Journal of Marketing*, 67 (4), 1–17.

Beaver, William, Paul Kettler, and Myron Scholes (1970), “The Association Between Market-Determined and Accounting-Determined Risk Measures,” *The Accounting Review*, 45 (October), 654-682.

Blume, Marshall E., Felix Lim, and Craig MacKinlay (1998), “The Declining Credit Quality of U.S. Corporate Debt: Myth or Reality?” *Journal of Finance*, 53 (4), 1389-1413.

Boulding, William, Eunkyu Lee, and Richard Staelin (1994), “Mastering the Mix: Do Advertising, Promotion, and Sales Force Activities Lead to Differentiation?” *Journal of Marketing Research*, 31 (2), 159–172.

Chan, Louis K. C., Jason Karceski, and Josef Lakonishok (2003), “The Level and Persistence of Growth Rates,” *Journal of Finance*, 58 (2), 643–684.

Copeland, Thomas E., John F. Weston, and Kuldeep Shastri (2013), *Financial Theory and Corporate Policy*. 4th ed. New Jersey: Pearson.

Demsetz, Harold (1982), “Barriers To Entry,” *American Economic Review*, 72 (1), 47.

Edeling, Alexander and Marc Fischer (2016), “Marketing's Impact on Firm Value: Generalizations from a Meta-Analysis", *Journal of Marketing Research*, forthcoming.

Erickson, Gary and Robert Jacobson (1992), “Gaining Comparative Advantage Through Discretionary Expenditures: The Returns to R&D and Advertising,” *Management Science*, 38 (9), 1264–1279.

Fang, Eric, Robert W. Palmatier, and Rajdeep Grewal (2011), “Effects of Customer and Innovation Asset Configuration Strategies on Firm Performance,” *Journal of Marketing Research*, 48 (3), 587-602.

Geroski, Paul A., Machin Stephen J., and Walters Christopher F. (1997), “Corporate Growth and Profitability”, *The Journal of Industrial Economics*, 45 (2), 171-189.

Greene, William H. (2012), Econometric analysis. 7th ed. Upper Saddle River, NJ: Pearson.

Himme, Alexander and Marc Fischer (2014), “Drivers of the Cost of Capital: The Joint Role of Non-Financial Metrics,” *International Journal of Research in Marketing*, 31 (2), 224-238.

Hou, Kewei and David T. Robinson (2006), “Industry Concentration and Average Stock Returns.” *The Journal of Finance*, 61 (4), 1927-1956.

Joshi, Amit and Dominique M. Hanssens (2010), “The Direct and Indirect Effects of Advertising Spending on Firm Value”, *Journal of Marketing*, 74 (1), 20–33.

Kemsley, Deen and Doron Nissim (2002), “Valuation of the Debt Tax Shield,” *Journal of Finance*, 57 (5), 2045-2073.

Kim, MinChung and Leigh M. McAlister (2011), “Stock Market Reaction to Unexpected Growth in Marketing Expenditure: Negative for Sales Force, Contingent on Spending Level for Advertising,” *Journal of Marketing*, 75 (4), 68-85.

Lustgarten, Steven and Stavros Thomadakis (1987), “Mobility Barriers and Tobin's q,” *The Journal of Business*, 60 (4), 519–537.

MacDonald, Glenn and Michael D. Ryall (2004), “How Do Value Creation and Competition Determine Whether a Firm Appropriates Value?” *Management Science*, 50 (10), 1319-33.

Matsumoto, Dawn A. (2002), “Management's Incentives to Avoid Negative Earnings Surprises,” *The Accounting Review*, 77 (3), 483-514.

McAfee, R. Preston and John McMillan (1995), “Organizational Diseconomies of Scale,” *Journal of Economics and Management Strategy*, 4 (3), 399–426.

Miller, Merton H. and Franco Modigliani (1961), “Dividend Policy, Growth, and the Valuation of Shares,” *Journal of Business*, 34 (4), 411-433.

Myers, Stewart C. (1977), “Determinants of corporate borrowing,” *Journal of Financial Economics*, 5 (2), 147-175.

Rappaport, Alfred and Michael J. Mauboussin (2001), *Expectations investing: Reading stock prices for better returns*. Boston: Harvard Business School Press.

Rao, Ramesh K.S. and Neeraj Bharadwaj (2008), “Marketing Initiatives, Expected Cash Flows, and Shareholder’s Wealth,” *Journal of Marketing*, 72 (1), 16-26.

Rego, Lopo L., Matthew T. Billett, and Neil A. Morgan (2009), “Consumer-Based Brand Equity and Firm Risk,” *Journal of Marketing*, 73 (6), 47–60.

Scherer, Frederic M. (1980), *Industrial Market Structure and Market Performance*. 2nd ed. Chicago: Rand-McNally.

Stickel, Scott. E. (1990), “Predicting Individual Analyst Earnings Forecasts,” *The Journal of Accounting Research*, 28 (2), 409-417.

Sobel, M. E. (1986), “Some new results on indirect effects and their standard errors in covariance structure models”, in N. Tuma (Ed.), *Sociological Methodology*, (159-186), Washington, DC: American Sociological Association.

Srivastava, Rajendra K., Tasadduq A. Shervani, and Liam Fahey (1998), “Market-Based Assets and Shareholder Value: A Framework for Analysis,” *Journal of Marketing*, 62 (1), 2–18.

Vorhies, Douglas W. and Neil A. Morgan (2005), “Benchmarking Marketing Capabilities for Sustainable Competitive Advantage.” *Journal of Marketing*, 69 (1), 80-94.

EIDESSTATTLICHE ERKLÄRUNG

nach § 6 der Promotionsordnung vom 16. Januar 2008

"Hiermit erkläre ich an Eides statt, dass ich die vorgelegte Arbeit ohne Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus anderen Quellen direkt oder indirekt übernommenen Aussagen, Daten und Konzepte sind unter Angabe der Quelle gekennzeichnet. Bei der Auswahl und Auswertung folgenden Materials haben mir die nachstehend aufgeführten Personen in der jeweils beschriebenen Weise entgeltlich/ unentgeltlich geholfen:

Weitere Personen – neben den in der Einleitung der Arbeit aufgeführten Koautorinnen und Koautoren - waren an der inhaltlich-materiellen Erstellung der vorliegenden Arbeit nicht beteiligt. Insbesondere habe ich hierfür nicht die entgeltliche Hilfe von Vermittlungs- bzw. Beratungsdiensten in Anspruch genommen. Niemand hat von mir unmittelbar oder mittelbar geldwerte Leistungen für Arbeiten erhalten, die im Zusammenhang mit dem Inhalt der vorgelegten Dissertation stehen. Die Arbeit wurde bisher weder im In- noch im Ausland in gleicher oder ähnlicher Form einer anderen Prüfungsbehörde vorgelegt. Ich versichere, dass ich nach bestem Wissen die reine Wahrheit gesagt und nichts verschwiegen habe."

Köln, 04. November 2016

CURRICULUM VITAE

Personal Information

Max Philipp Backhaus
Limburger Straße 31
50672 Köln
backhaus@wiso.uni-koeln.de
+49 171 3504402
http://www.marketing.uni-koeln.de

Education

Since 03/2012	**University of Cologne** Research assistant and PhD student at the Department of Marketing and Marketing Research (Chair: Prof. Dr. Marc Fischer) Dissertation: "Econometric Essays on Protecting, Benefiting, and Growing from Customer-Based Brand Equity"
2008 – 2011	**NHH Bergen, Norway and University of Cologne** CEMS Master of International Management
2005 – 2010	**University of Cologne** Studies of Business Administration ▪ Major: Supply Chain Management, Corporate Finance, Statistics ▪ Degree: Dipl.-Kfm. (Grade 1.4)
2005	**Ratsgymnasium Münster** Abitur (Grade 1.6)
2002-2003	Robert Louis Stevenson High school, Pebble Beach, USA

Industry Experience

Since 03/2012	**Chair for Marketing and Market Research | University of Cologne** Research and Teaching Assistant (Chair: Prof. Dr. Marc Fischer) ▪ Course work: Service and Media Marketing, Marketing Engineering, Business Projects and Seminars ▪ Advisor for numerous bachelor and master theses ▪ Assistance in the conception of the new WiSo-Faculty marketing master program
Since 08/2012	**Freelance Consulting and Market Research | Cologne**
2011 – 2012	**The Boston Consulting Group | Cologne** Associate consultant ▪ Various national and international projects within financial services and investment banking ▪ Member of the BCG Risk Taskforce
01/2009 – 04/2009	**Allianz AG | Minneapolis, USA** Internship Investment Management ▪ Capital and liquidity management ▪ Real Estate Investment analysis

09/2007 – 10/2007	**KPMG | Düsseldorf** Internship Business Performance Services ▪ Optimization of the annual reporting process of a leading German logistic firm
04/2007 – 07/2008	**Chair for Econometrics and Statistics | University of Cologne** Student assistant (Chair: Prof Dr. Schmid)
08/2006 – 10/2008	**Fiege | Greven** Internship Controlling Department ▪ Reorganization of the IT reporting landscape
08/2005 – 10/2005	**The Boston Consulting Group | Düsseldorf** Internship Knowledge Group ▪ Market research with focus on global steel market demand and supply

Research Interests

Topics	Brand Management, Marketing Response Modeling, Marketing Finance
Methods	Time-series and Panel Data Analysis, Diffusion Modeling

Honors and Awards

Winner	2015 SMA Doctoral Dissertation Proposal Competition
Runner-Up	2015 AMS Mary Kay Doctoral Dissertation Proposal Competition

Working Paper and Conference Presentations

Backhaus, Max and Marc Fischer, "Brand damage from Product Harm and Corporate Social Irresponsibility – How deep and how long?" (2016), under revision (2nd round, *Journal of Marketing Research*), presented at the 36th INFORMS Marketing Science, Conference, Atlanta, USA (2014), forthcoming as *MSI Working paper*.

Fischer, Marc, Max Backhaus, and Hornig, Tobias, "Valuing Growth: How Marketing Contributes to Value From Future Profit Growth" (2016), under revision, *Management Science*.

Backhaus, Max, Lügger, Kai and Robert Wilken (2014), "Accelerating Innovations: When Do They Pay Off? ", in Proceedings of the 43rd EMAC Conference, Valencia/Spain.

Backhaus, Max, "Do Layoffs Hurt a Firm's Brand? – An Event Study with Consumer Mindset Metrics" (2016), Working Paper.

Software

Microsoft Office
STATA, LIMDEP, SPSS, EVIEWS

Extracurricular Activity

Since 2008	**PIM & CEMS Club Köln & Köln Alumni**
Since 1995	**DLRG Münster (German Lifeguard Association)**

Cologne, 4th November 2016