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“Business Cycles and Consumer Behavior”

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Synopsis

"I've heard there's going to be a recession.

I've decided not to participate."

Walt Disney

1 Introduction

The concept of business cycles has a long history in the economic literature. The classic and often cited definition of business cycles goes back as far as to the pioneering work provided by Burns and Mitchel (1946, p. 3), who state: "A cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of change is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years." Two key characteristics of business cycles mentioned in this definition make the relevance of business cycles quite evident. First, business cycles have a far-reaching impact on various economic activities. The Business Cycle Dating Committee of the National Bureau of Economic Research (NBER), that maintains a chronology of the U.S. business cycle, states economic expansions and contractions to be visible in real Gross Domestic Product (GDP), real income, employment, industrial production, as well as wholesale-retail sales (NBER 2008). Thus, business cycles in some way affect a variety of economic participants. Second, business cycles are ever recurrent. The Business Cycle Dating Committee documents eleven full cycles for the US economy since 1945.[1] Hence, economic expansions and contractions appear to be an ever-present force, as demonstrated in the recent

[1] An overview of US business cycle expansions and contractions is available here: https://www.nber.org/cycles.html

past by the devastating impact of the so called "Great Recession" that began in 2007 and lasted until 2009.

When economic conditions turn sour, consumers' urge to economize on daily expenses increases extensively, with obvious consequences for retailers and manufacturers. *The Economist* (2011) estimated that the Great Recession led to an 8%, or $4,000, decrease in real annual spending among U.S. households, which amounts to $500 billion in foregone revenues. The substantial reduction of buying power has led consumers to tighten their belts in many ways, ranging from spending less on cloth and housing to food and alcoholic beverages. However, business cycles and their far reaching impact have for a long time been overlooked by marketing researchers. Instead, they have traditionally received extensive but exclusive attention in the economic domain. Therein, studies primarily focus rather on the aggregate macroeconomic impact on entire countries (e.g., Christiano and Fitzgerald 1998; Zarnowitz 1985). Yet what is happening on the aggregate economic level of a country is not necessarily representative of what is happening on the industry level, not to mention individual firm, brand, or household level. A famous quote by Walt Disney - founder of The Walt Disney Company - illustrates this in a striking way: "I've heard there's going to be a recession. I've decided not to participate." Even though being a bold statement, Disney's attitude towards adverse economic conditions demonstrates that the economists' limited view on the aggregate impact on entire countries falls short of what marketing researchers have also been intrigued by to observe during the latest downturns. In fact, not all firms, brands, or households are affected to the same extent, nor do they react in the same way when being faced with changing macroeconomic conditions. Thus, although aggregate consumer spending typically declines in economic recessions and consumers start to re-allocate their budgets towards less expensive product alternatives, there are cases of counter-cyclical behavior, too.

The most prominent example in this regard is known as the “lipstick effect” (Nelson 2001). During 2008, when the rest of the economy was struggling with record declines in sales, L’Oréal - one of the world’s largest cosmetic companies - experienced a sales growth by 5.3% (Elliot 2008). The idea behind the lipstick effect, that consumers will be more willing to buy small and less costly luxury goods in times of economic hardship, is even believed to be traced back to the Great Depression (1929 to 1933), when sales of cosmetic products also grew unexpectedly (Koehn 2011). Relying on historical spending data and controlled experiments, Hill et al. (2012) lately have shown empirical evidence for the existence of the lipstick effect and attribute its root causes to evolutionary psychology.

Lipsticks or cosmetics in general, however, are not the only product examples that are associated with counter-cyclical consumer behavior. Market analysts state that movie attendance in the U.S., for instance, increased by nearly 16% during the Great Recession (Cieply and Barnes 2009). Similar trends have been observed for books in Europe, where sales jumped by 2.3% in Germany and 2.4% in France at the beginning of 2009 (Pfanner 2009). Both movies and books constitute relatively cheap forms of entertainment which make them attractive alternatives to more expensive forms of amusement during tough economic times. With unemployment on the rise and declining working hours, people may also unintentionally spent more time at home and feel the urge to forget their troubles by escaping the depressing reality into fiction. Further, shoppers may get tired of pinching pennies and delaying gratification, even, or especially, when it comes to everyday necessities like grocery shopping. Extreme restrictiveness to less expensive product alternatives can often lead to a condition known as “frugal fatigue” (Winsight Grocery Business 2012). The impulse for frivolous indulgence after some time is particularly strong among those who tended not to be particularly frugal in the first place.

Driven by such extensive behavioral changes at the consumer level that also force marketers to reconsider, and even turn around, their usual business activities, business cycles have caught marketing researchers' attention in the last two decades. Economic downturns in the early and late 2000's have certainly contributed to and set the research context for many studies. In a recent literature review on business cycle research in marketing, Dekimpe and Deleersyder (2017) have identified 31 post-2000 marketing studies that focus on the impact of business cycles. However, the authors also have called for further broadening the scope of research. Although the number of research studies has increased substantially over the last two decades, the number of distinct research questions has been left behind. Many studies, undeniably, have a fairly similar focus. Shifts in grocery shopping during tough economic times, for instance, have been extensively documented with regard to private labels (e.g., Deleersnyder et al. 2009; Dubé, Hitsch, and Rossi 2018; Lamey 2014; Lamey et al. 2007, 2012; Ma et al. 2011). Studies on marketing conduct and the effectiveness of marketing instruments have primarily focused on pricing (e.g., Estelami, Lehmann, and Holden 2001; Gordon, Goldfarb, and Li 2013; Sudhir, Chintagunta, and Kadiyali 2005; Van Heerde et al. 2013) or advertising (Deleersnyder et al. 2009; Graham and Frankenberger 2011; Lamey et al. 2012; Özturan, Özsomer, and Pieters 2014; Sethuraman, Tellis, and Briesch 2011; Srinivasan, Lilien, and Sridhar 2011; Steenkamp and Fang 2011; Tuli, Mzkherjee, and Dekimpe 2012; Van Heerde et al. 2013).

Accordingly, this dissertation takes up the call for more research on business cycles in marketing by Dekimpe and Deleersnyder (2017). Thereby, it extends and contributes to existing research with three empirical papers. Table 1 presents a short overview of the three dissertation papers.

Table 1: Overview of Dissertation Papers

Paper	Title	Author(s)
I	What Chatter Matters in Times of Economic Change? The Impact of Consumer Confidence on eWOM Effectiveness	Thomas P. Scholdra
II	Shifts Beneath the Surface: How Micro- and Macroeconomic Conditions Affect FMCG Shopping Strategies	Thomas P. Scholdra, Julian R. K. Wichmann, Maik Eisenbeiß, Werner J. Reinartz
III	Ratings, Reviews, and Recessions: How Business Cycles Shape Online Opinion	Thomas P. Scholdra

The following section provides a more detailed overview of the underlying domain of business cycles in marketing and clarifies how each dissertation paper ties into existing research studies and adds to them.

2 Research Domain

This dissertation is rooted in the domain of business cycle research in marketing even though Paper I and Paper III also refer to literature on electronic word of mouth (eWOM) effectiveness (e.g., Chevalier and Mayzlin 2006) and online opinion formation (e.g., Godes and Silva 2012). Dekimpe and Deleersnyder (2017) distinguish three streams of research in their literature review that are prevalent in the business cycle research domain. The first stream focuses on how performance measures vary across different stages of the business cycle (e.g., Deleersnyder et al. 2004; Lamey et al. 2007). The second stream evaluates how marketing conduct changes over the business cycle (e.g., Deleersnyder et al. 2009; Srinivasan, Rangaswamy, and Lilien 2005). Finally, a third stream is concerned with the differential effectiveness of various marketing investments across alternative business cycle phases (e.g., Estelami, Lehmann, and Holden 2001; Grewal and Tansushaj 2001). As the overall objective

of this dissertation is to investigate the far-reaching influence of business cycles on consumer behavior, the dissertation is mostly related to the first and third stream of research. However, to underline the consumer centric perspective adopted in this dissertation, I structure relevant literature according to the three phases of the customer experience process that comprises prepurchase, purchase, and postpurchase behaviors (Lemon and Verhoef 2016).

The prepurchase phase encompasses all aspects of the consumer's experience from the need, goal, or impulse recognition to the consideration of satisfying that need, goal, or impulse with a purchase (Hoyer 1984). Relevant brand-owned touchpoints in this phase are all brand-owned media (e.g., advertising, websites, loyalty programs) and brand owned elements of the marketing mix (e.g., product attributes, service, price) (Lemon and Verhoef 2016). The business cycle literature in this regard focuses predominantly on the changing effectiveness of marketing instruments such as investments in research and development (Srinivasan, Lilien, and Sridhar 2011; Steenkamp and Fang 2011), service attributes (Hunneman, Verhoef, and Sloot 2015), customer loyalty strategies (Ou et al. 2014), pricing (Estelami, Lehmann, and Holden 2001; Gordon, Goldfarb, and Li 2012), or advertising (Graham and Frankenberger 2011; Sethuraman, Tellis, and Briesch 2011; Srinivasan, Lilien, and Sridhar; Steenkamp and Fang 2011; Tuli, Mukherjee, and Dekimpe 2012; Van Heerde et al. 2013). To date, there is only one study by Dhar and Weinberg (2016) that deviates from the usual focus on brand-owned touchpoints and considers movie critics' ratings as an external touchpoint and third-party information source for consumers in the prepurchase phase. Paper I of this dissertation ties in at this point and sheds light on the changing effectiveness of eWOM as earned media over the business cycle.

Following, the purchase phase of the customer experience process covers all customer interactions with a brand and its environment during the purchase, which is characterized by consumer behaviors such as choice, ordering, and payment (Lemon and Verhoef 2016). Therefore, the retail store itself may constitute a concentration of the most important

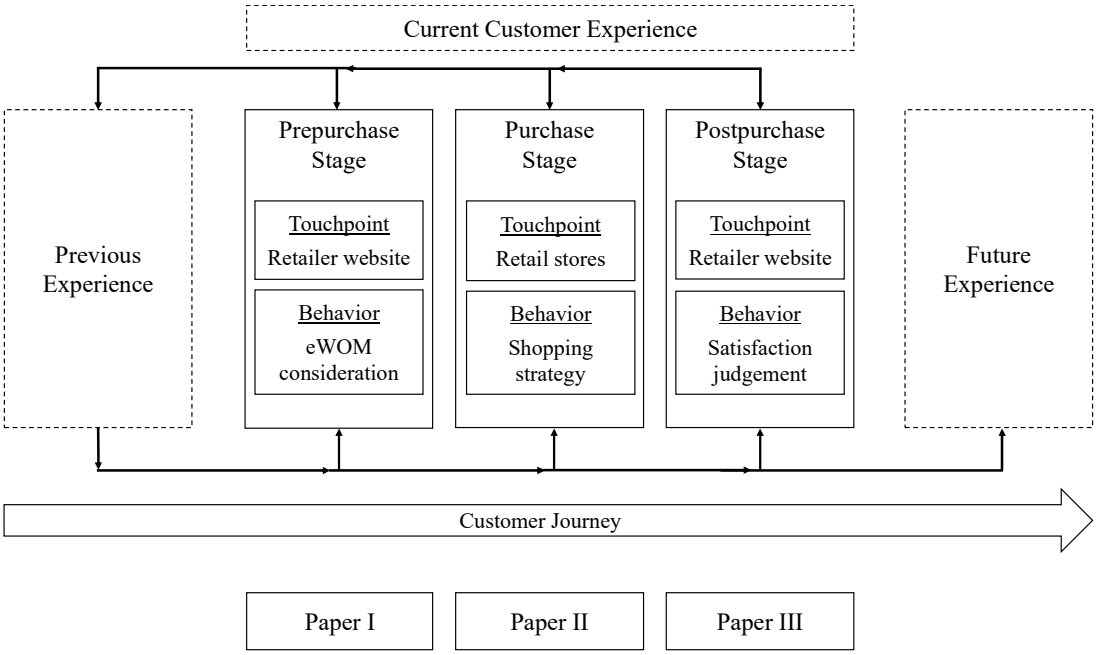
touchpoints in this phase like brands, assortments, and prices. Business cycle research in this regard has focused either on consumers' deterioration of spending in specific product categories (Deleersnyder et al. 2004; Dutt and Padmanabhan 2011; Kamakura and Du 2012) and industries (Dekimpe, Peers, and Van Heerde 2016), or consumers' changing shopping preferences for specific brand types (Cha, Chintagunta, and Dhar 2015; Dubé, Hitsch, and Rossi 2018; Lamey et al. 2007; Ma et al. 2011), store formats (Cha, Chintagunta, and Dhar 2015; Lamey 2014; Ma et al. 2011), and price tiers (Cha, Chintagunta, and Dhar 2015; Ma et al. 2011). However, shifts in consumer shopping preferences have been analyzed in isolation and potential interdependencies were widely neglected. Paper II of this dissertation provides a comprehensive conceptualization of shopping strategies and reveals respective adjustments of such strategies in the face of changing economic conditions.

Finally, the postpurchase phase of the customer experience process encompasses customer interactions with the brand and its environment following the actual purchase, which includes behaviors such as usage and consumption, postpurchase engagement, and service requests (Lemon and Verhoef 2016). Surprisingly, relatively little attention has been given to such or related postpurchase behaviors in the business cycle domain. Only few studies have considered how the impact of/on customer satisfaction changes over the business cycle (Fornell, Rust, and Dekimpe 2010; Hunneman, Verhoef, and Sloot 2015; Kumar et al. 2014; Yeung et al. 2013). One reason might be that longitudinal, survey-based data on individual customer satisfaction is difficult and costly to obtain. Paper III of this dissertation considers online product reviews to be a valid and easily accessible representation of consumers' satisfaction with a product and demonstrates how this satisfaction judgement is affected by business cycle fluctuations.

3 Research Outline

This dissertation comprises three empirical papers that advance our knowledge about the comprehensive impact of business cycles on consumer behavior. Figure 1 provides an overview of the research outline and shows how each paper ties into distinct parts along the customer journey.[2] Importantly, all three papers combine unique sets of online as well as offline touchpoints and consumer behaviors that are particularly relevant in the respective prepurchase, purchase, and postpurchase stage. Furthermore, all three papers combine several different types of data with different methodological approaches to achieve their individual research objectives. Table 2 provides an extended overview of the three dissertation papers.

Figure 1: Research Outline



Own illustration (2019) following Lemon and Verhoef (2016).

[2]An in-depth review of customer experiences throughout the customer journey is provided by Lemon and Verhoef (2016)

Paper I titled *"What Chatter Matters in Times of Economic Change? The Impact of Consumer Confidence on eWOM Effectiveness"* (by Thomas P. Scholdra), investigates the moderating influence of consumer confidence on the relationship between electronic word of mouth (eWOM) and sales. The empirical study is based on a unique and longitudinal product level data set, containing weekly sales-rank, price, and eWOM information from Amazon.com and macroeconomic data from the University of Michigan - Surveys of Consumers. The data covers a total time span from 2010 to 2014 and two product categories. Three key eWOM characteristics are considered - namely eWOM value, volume, and variance - that accommodate distinct informational signals about a product for potential buyers in the prepurchase phase. Using a first-difference estimation approach, this study is the first to comprehensively demonstrate the changing effectiveness of these eWOM characteristics for consumers' decision making process in the light of varying economic conditions.

Paper II titled *"Shifts Beneath the Surface: How Micro- and Macroeconomic Conditions Affect FMCG Shopping Strategies"* (by Thomas P. Scholdra, Julian R. K. Wichmann, Maik Eisenbeiß, and Werner J. Reinartz) turns the attention towards consumer purchase behavior in the German FMCG context. Herein, existing variety in households' shopping strategies and respective switches of strategies are identified when changes in individual income (i.e., microeconomic conditions) or general business cycle fluctuations (i.e., macroeconomic conditions) are prevalent. Shopping strategies are comprehensively conceptualized as individual household preferences for store formats, brand types, and price tiers, which constitute pivotal, price-related adjustment opportunities when economizing is needed. Combining transaction and socio-demographics data from the GfK Germany ConsumerScan panel, Nielsen advertising data, and macroeconomic data from the German Federal Statistical Office, a unique and longitudinal data set is created that represents purchase behavior of more than 5000 households over the time period of 2006 to 2014. Seven distinct shopping strategies

and respective switches between them are identified based on a dynamic hidden Markov model (HMM) approach and a simulation study.

Finally, Paper III titled *"Ratings, Reviews, and Recessions: How Business Cycles Shape Online Opinion"* (by Thomas P. Scholdra) investigates the impact of economic expansions and contractions on consumers' postpurchase satisfaction judgement expressed in the online opinion section of a retailer website. Review level data from the books category of Amazon.com is combined with macroeconomic information from the U.S. Bureau of Economic Analysis (BEA) to create a longitudinal data set spanning from 1996 to 2014. Two measures of expressed online opinion are considered - the numeric review rating as well as review text sentiment - and ordinal logistic regressions and linear regressions respectively applied in the empirical study. Further attention is drawn to product popularity as potential moderating force. This study is the first to demonstrate the distinct effects economic expansions and contractions have on consumers' opinion expressions in online environments.

Table 2: Extended Overview of Dissertation Papers

Paper	Title	Publication status	Key objectives	Data	Method
I	"What Chatter Matters in Times of Economic Change? The Impact of Consumer Confidence on eWOM Effectiveness" *Author:* *Thomas P. Scholdra*	Working Paper	• Investigate how changes of consumer confidence influence the effectiveness of eWOM valence, volume, and variance in driving sales.	*Type:* • Sales-ranks and prices • Product reviews • Index of Consumer Sentiment *Source:* • Amazon.com • 3rd-party price/sales tracking websites • University of Michigan	• First-difference OLS regression
II	"Shifts Beneath the Surface: How Micro- and Macroeconomic Conditions Affect FMCG Shopping Strategies" *Authors:* *Thomas P. Scholdra, Julian R. K. Wichmann, Maik Eisenbeiß, Werner J. Reinartz*	In preparation for submission to the *Journal of Marketing*	• Identify and characterizing distinct shopping strategies based on households' brand type, store format, and price tier preferences. • Investigate how households switch among shopping strategies, i.e., which strategies they are abandoning and which ones they are adopting as a result of changing micro- and macroeconomic conditions. • Determine the sensitivity of each shopping strategy to changes in micro- and macroeconomic conditions.	*Type:* • Transactions and sociodemographics • Advertising spending • Gross domestic product *Source:* • GfK Germany ConsumerScan panel • Nielsen Company • Federal Statistical Office Germany	• Hidden Markov model
III	"Ratings, Reviews, and Recessions: How Business Cycles Shape Online Opinion" *Author:* *Thomas P. Scholdra*	Working Paper	• Investigate how economic expansions and contractions impact numeric ratings and review sentiment in online product reviews. • Determine the moderating role of product popularity in the business cycle-online opinion relationship.	*Type:* • Product reviews • Gross domestic product *Source:* • Amazon.com • US Bureau of Economic Analysis	• Ordinal logistic regression • OLS regression

Notes: FMCG= fast-moving consumer goods; OLS = ordinary least squares; EWOM = electronic word of mouth

4 Summary of Dissertation Papers

The following section includes a comprehensive summary of each of the three dissertation papers. Each summary describes the respective paper's motivation, objectives, approach, key findings, and contribution.

4.1 Paper I

What Chatter Matters in Times of Economic Change? The Impact of Consumer Confidence on eWOM Effectiveness

Author: Thomas P. Scholdra

Crisis-hit consumers tend to behave differently from those experiencing economic prosperity (Ang, Leone, and Kotler 2000; Dutt and Padmanabhan 2011). They are not only more sensitive with regard to spending in particular industries or categories (e.g., Deleersnyder et al. 2004) or exhibit distinct strategies to cope with adverse economic conditions (e.g., Dutt and Padmanabhan 2011), but also react differently to specific marketing instruments such as advertising (Graham and Frankenberger 2011; Van Heerde et al. 2013) or pricing (Gordon, Goldfarb, and Li 2013; Van Heerde et al. 2013). However, while existing studies have almost exclusively focused on the effectiveness of company-owned marketing instruments, potentially other important sources of information for consumers that are known as earned media (Stephen and Galak 2012) - such as electronic word of mouth (eWOM) - have been widely neglected.

This lack of attention is surprising given the prevalence and popularity of eWOM, particularly in consumers' prepurchase activities. Babić et al. (2016) define eWOM as the act of consumers to provide information about goods, services, brands, or companies to other consumers through the Internet. Such information may be accessible through various ways, e.g., blog posts, tweets, or product reviews and ratings on opinion platforms. Potential buyers

actively seek and trust such eWOM sources during their decision making process. Around 90% of consumers consult eWOM in form of online product reviews before visiting a business and 88% of consumers trust such eWOM sources as much as personal recommendations (Saleh 2015). Thus, consumers specifically use eWOM as an effective tool to learn about the quality of products (Zhao et al. 2013) or their own preferences (Wu et al. 2015), resulting in a reduction of uncertainty about the purchase by identifying products that best match their idiosyncratic usage conditions (Chen and Xie 2008). A fact that matters even more when overall spending deteriorates during tough economic times.

EWOM is of particular relevance for firms too. Previous studies have shown that eWOM potentially has an impact on sales (Chevalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010) or that firms may be able to successfully incorporate eWOM to enrich their marketing strategies (Chen and Xie 2008; Cui, Lui, and Guo 2012). Indeed, marketers nowadays actively try to harness eWOM as a marketing tool and, for instance, invite consumers to submit product reviews to respective opinion platforms (Dellarocas 2003). Knowledge about potential shifts in the effectiveness of eWOM due to changing economic conditions should accordingly be of great interest for marketers. During the Great Recession, for instance, the U.S. coffeehouse chain Starbucks discovered its customers to be fatigued by premium priced coffee and to increasingly defect to cheaper but good-enough competitors. This erosion of loyalty has significantly been accelerated by the instantaneous spread of accompanying eWOM (Flatters and Willmott 2009). The goal of this study therefore is to pursue the following research objective:

- Investigate how changes of consumer confidence influence the effectiveness of eWOM valence, volume, and variance in driving sales.

We consider three metrics that have been identified by previous research to capture different aspects of eWOM. These metrics are eWOM volume (i.e., the total amount in eWOM

interactions), valence (i.e., the positivity or negativity in eWOM interactions), and variance (i.e., the heterogeneity in eWOM interactions). We construct a unique and longitudinal data set on the product level, containing weekly sales-rank, price, and eWOM information from different sources, covering a total time span from 2010 to 2014 and two product categories. To investigate the moderating role of the economic environment, we include consumer confidence as a proxy for consumers' perceptions of the prevailing economic conditions. Concretely, we use the publically available Index of Consumer Sentiment (ICS) which is published by the University of Michigan - Survey of Consumers. Overall, we thus build an encompassing data set that combines behavioral measures with market data and aggregate economic information.

We base our estimation process on a first-difference approach which has been frequently used in the eWOM literature (Babić et al. 2016) to account for potential endogeneity issues (Wooldridge 2002). Our results reveal that increasing eWOM valence and variance have positive effects on incremental sales, while price exhibits a negative effect. Importantly, the effectiveness of these two eWOM metrics in driving incremental sales depends on the prevailing change in consumer confidence. Concretely, improving economic conditions, as represented by an increase in consumer confidence, diminish the positive impact of eWOM valence and variance on incremental product sales. Thus, increasing eWOM valence and variance are more effective when the economy is in a downturn. Importantly, because we control for potential product price changes, these results can be regarded as independent of any price effects. Moreover, price changes in our focal product categories do not exhibit any differential effects over the course of changing economic conditions. Therefore, eWOM value and variance may be considered more effective in driving sales performance during economic downturns than pricing does. These results extend existing knowledge from the business cycle literature that states consumers to be rather price than quality oriented during economic downturns (Gordon, Goldfarb, and Li 2013; Lamey et al. 2012; Van Heerde et al. 2013).

The fact that increasing eWOM valence and variance are more effective in driving incremental sales during economic downturns is particularly valuable for marketers. It makes eWOM in general an attractive means for counter-cyclical marketing activities. Indeed, marketers nowadays actively try to harness eWOM as a marketing tool and invite consumers to submit their product evaluations to respective opinion platforms (Dellarocas 2003). Our results suggest to further strengthen such activities when the economy goes down. Thereby, particularly those products outside the top rankings and with consistently lower ratings exhibit the largest potential for significant sales gains. That is, when positive eWOM not only increases the mean rating of a product in a substantial way, but also the variance among existing ratings. Furthermore, our results reveal that price changes in the focal categories do not exhibit similar variation in effectiveness over changing economic conditions. Therefore, pricing decisions should be set aside in this particular case and available marketing budgets should be re-allocated to potential eWOM campaigns.

4.2 Paper II

Shifts Beneath the Surface: How Micro- and Macroeconomic Conditions Affect FMCG Shopping Strategies

Authors: Thomas P. Scholdra, Julian R. K. Wichmann, Maik Eisenbeiß, and Werner J. Reinartz

Households make nearly daily purchases, yet the economic conditions under which they make purchases change constantly. These changing conditions might take place on a personal, microeconomic level, such as if the principal earner of a household receives a pay raise or, contrarily, a household member loses a job. Furthermore, they also might reflect the macroeconomic business cycle with its reoccurring expansions and contractions, as recently highlighted by the Great Recession or the European debt crisis. These changing micro- and macroeconomic conditions substantially affect household spending and, in turn, companies' profits. *The Economist* (2011) estimated that the Great Recession led to an 8%, or $4,000, decrease in real annual spending among U.S. households, which amounts to $500 billion in foregone revenues. While in some product categories like durables households tend to postpone purchases until economic conditions improve (Deleersnyder et al. 2004; Dutt and Padmanabhan 2011), for fast moving consumer goods (FMCGs) postponing purchases oftentimes is not possible. Consequently, households must find ways to economize on the prices they pay to generate savings (Dekimpe and Deleersnyder 2017).

Prior research identifies three distinct shopping preferences that households adjust when being faced with economic conditions that require them to reduce spending: They adjust their brand type preference by switching from national brands (NBs) to cheaper brands or private labels (PLs) (Cha, Chintagunta, and Dhar 2015; Dubé, Hitsch, and Rossi 2018; Lamey et al. 2007; Ma et al. 2011), their store format preference by switching from supermarkets to less expensive discounters (Cha, Chintagunta, and Dhar 2015; Lamey 2014; Ma et al. 2011), and

their price tier preference by switching from regular to promotional prices (Cha, Chintagunta, and Dhar; Ma et al. 2011). However, by investigating how households react to changing macro- and microeconomic conditions at large, this literature stream has "taken a fairly aggregate view" (Dekimpe and Deleersnyder 2017, p. 7) on households and their preference adjustments. For example, Dubé, Hitsch, and Rossi (2018) find that households increase PL purchases during recessions. However, we do not know whether all households do so or if differences exist across households in terms of which of the other shopping preferences they adjust.

This, however, is particularly important in the context of FMCG shopping, because each household may exhibit a different combination of shopping preferences for brand types, store formats, and price tiers. Where one household may primarily shop for NBs on promotion in supermarkets, another household may prefer PLs in supermarkets or may focus on purchasing NBs primarily from discounters. These distinct combinations of shopping preferences constitute what we define as shopping strategies. To implement these widely varying shopping strategies, households also undertake vastly different adjustments to realize savings when macro- or microeconomic conditions change. Where one household may retain its store format preference for supermarkets but adjust its brand type preference and purchase more PLs within this store format, a household that already purchases mostly PLs in supermarkets is forced to make different adjustments. One option would be to adjust the store format preference and increasingly shop in discounters. These idiosyncratic adjustments constitute switches from one shopping strategy into another. Yet even households with the same initial shopping strategy could realize savings through different means.

For manufacturers and retailers, this vast variety of possible adjustments means that when macro- and microeconomic conditions change, the resulting complex transformations of their customer bases are difficult to detect. Taking the firm's perspective, it is therefore not only critical to know whether households adjust their shopping strategy but also which previous

strategy they are coming from and which they are switching to. Ignoring such contingencies and changes to the customer base may result in an ineffective marketing mix and loss of market share in the long run.

To identify the various shifts that may take place beneath the surface, as caused by changing macro- and microeconomic conditions, we pursue three foundational research objectives:

- Identify and characterize distinct shopping strategies based on households' brand type, store format, and price tier preferences.
- Investigate how households switch among shopping strategies, i.e., which strategies they are abandoning and which ones they are adopting, as a result of changing micro- and macroeconomic conditions.
- Determine the sensitivity of each shopping strategy to changes in micro- and macroeconomic conditions.

For these purposes, we rely on the German grocery retail market as our empirical setting. It reached €183.5 billion in sales revenues and a growth rate of 3.5% in 2017, signaling the largest jump in its steady growth trend since the financial crisis (GfK 2017). Discounters are the dominant store format, accounting for 42.7% of the market's value, ahead of supermarkets, hypermarkets, and drugstores. The market also is highly concentrated, particularly in the supermarket format, where the retailers Edeka and Rewe account for over 90% of sales revenues (Kantar Consulting 2018). In their attempts to confront the market power of discounters and appeal to more shoppers, supermarkets have evolved to primary promoters of PLs in recent years. They now account for 37.4% of that market's value (GfK 2017).

To reflect the particular characteristics of the German grocery retail market, our data set combines several sources and information across distinct levels of aggregation. The primary data source is the ConsumerScan panel, provided by GfK Germany, which includes transaction

and survey data for panelists at the individual household level. As a major advantage, the ConsumerScan panel covers private consumption comprehensively and representatively, including all German food retailers, specialty stores, drugstores, and discount stores that typically do not offer data for market research purposes through retail panels. The inclusion of such data, however, is particularly crucial, considering the substantial market share of discount stores in Germany. The panel also contains survey data for all panelists, based on self-reported annual information (age, household size, income). We control for advertising effects by obtaining weekly data about brand-level advertising spending across multiple channels for all major manufacturers and retailers from the Nielsen Company. Finally, publically available gross domestic product (GDP) data from the Federal Statistical Office is used to indicate the aggregate economic situation. Overall, we thus build a unique, encompassing data set that combines behavioral measures with survey-based household demographics, aggregated economic measures, and brand-level advertising data.

To achieve our objectives of identifying specific shopping strategies and uncovering switching patterns among them, we specify an HMM to classify households into latent states of shopping behavior and allow for transitions across these latent states over time. We assume that each latent state represents a specific shopping strategy, characterized by the household's observable discounter share of wallet (SOW), discounter PL SOW, supermarket PL SOW, and price promotion SOW. We assign each household to one latent state in the beginning of the time series and note if they transition into different latent states, driven by their individual micro- and general macroeconomic conditions.

Our results reveal seven shopping strategies with distinct characteristics in terms of store, brand type, and price tier preferences: *Conventional Shopping, Supermarket Shopping, Supermarket PL Picking, Discounter Shopping, Discounter Brand Picking, Brand Shopping,* and *Cherry Picking.* Conventional Shopping dominates, accounting for 52% of all observations

and featuring balanced discounter SOW, PL SOW, and price promotion SOW, but distinct and diverse strategies make up the other half. Two strategies are characterized by a large proportion of spending with discounters and differ primarily in terms of their discounter PL SOW (Discounter Shopping and Discounter Brand Picking). The other four shopping strategies all feature similar discounter SOW but differ in their supermarket PL SOW (Supermarket PL Shopping, Supermarket Shopping, and Brand Shopping) or price promotion SOW (Cherry Picking).

Furthermore, households switch among these shopping strategies in response to micro- or macroeconomic conditions. Depending on a household's prior shopping strategy, it adopts certain adjustments, though households with the same initial shopping strategy also may pursue different adjustments with contrary effects on shopping preferences. Importantly, these specific effects would remain hidden in an aggregate analysis. For example, lower household income leads some households to adopt a shopping strategy in which they spend more at supermarkets, while others spend more at discounters. Notably, households make adjustments during adverse macroeconomic conditions even if they suffer no income losses. On a more practical level, households exhibit strong preferences for NBs even when microeconomic conditions worsen and adjust by purchasing more NBs from discounters or on promotion. Furthermore, purchasing NBs in supermarkets represents a ceiling strategy across households that they adopt when microeconomic conditions improve. However, we do not observe a mirror effect of PL purchases in discounters when conditions worsen. Thus, some households remain reluctant to purchase PLs from discounters even in poor conditions.

In conclusion, our results reveal the existence of various shopping strategies and highlight how households switch strategies as a result of changing micro- and macroeconomic conditions. Although manufacturers and retailers have little control over these events, knowledge about the associated reactions by households allows them to optimize their

marketing mix. NB manufacturers, for instance, experience increasing purchases of NBs from discounters and on price promotion, even though NB may lose market share as a whole when households experience income reductions. Therefore, NB manufacturers could increase their price promotion activities, catering to households that switch strategies from Brand Shopping to Cherry Picking. This switch even tends to increase households' spending; they purchase greater volumes and end up spending more in total with this strategy. Additionally, NB manufacturers could increase listings in discount store formats to cater to households that switch to the Discounter Brand Picking strategy. When conditions improve for households, whether on a micro- or macroeconomic level, they tend to adopt strategies with higher NB SOW. Therefore, NB managers should reallocate their budgets, according to favorable versus unfavorable conditions. Supermarkets, in contrast, lose market share to discounters, but still enjoy an increase in PL purchases when households experience income reductions. Strengthening their PLs would give supermarket managers leverage over NB managers when negotiating prices, promotional activities, and advertising allowances. These managers also might want to increase their advertising spending during adverse conditions, with the dual purpose of strengthening their store image and their PLs. Line extensions to their PLs also could help supermarkets cater to the households considering a switch to Supermarket Shopping or Supermarket PL Picking, which households switch to when they move away from the Conventional Shopping strategy, for instance. Finally, discounters stand to gain from adverse microeconomic conditions, because households switch to the Discounter Brand Picking and Discounter Shopping strategies. Working with NBs, discounters can extend their NB portfolio to increase switches to the Discounter Brand Picking strategy. However, discounters also should allocate some spending to periods associated with economic expansions, to keep households from switching back to supermarkets.

4.3 Paper III

Ratings, Reviews, and Recessions: How Business Cycles Shape Online Opinion

Author: Thomas P. Scholdra

Consumers tend to behave differently during economic downturns than during economic upturns (Ang, Leone, and Kotler 2000; Dutt and Padmanabhan 2011). And the US economy has gone through some particularly turbulent times considering the early 2000s recession or the Great Recession from 2007 to 2009. Prior research has proven a far-reaching impact of changing economic conditions on consumers, in particular on their behavior prior to and during purchase. Higher price knowledge (Estelami, Lehmann, and Holden 2001) and increased purchase planning (Hampson and McGoldrick 2013) are only two examples of how consumers adapt before making purchases. Consumers also tend to reduce or postpone purchases altogether, particularly in categories like durables (e.g., Deleersnyder et al. 2004; Dutt and Padmanabhan 2011) or non-essential goods and services (e.g., Kamakura and Du 2012) until economic conditions improve. In other product categories, consumers rather reallocate their spending towards more affordable brand types (e.g., Dubé, Hitsch, and Rossi 2018; Lamey et al. 2007), store formats (Lamey 2014), or items being offered on temporary price reduction (Cha, Chintagunta, and Dhar 2015; Ma et al. 2011).

However, despite the apparently far-reaching impact of business cycles on consumer behavior, their importance for and impact on consumers' postpurchase behavior in particular has been widely neglected by existing research. Only recently, researchers started to link macroeconomic variables with postpurchase outcomes like consumer satisfaction. (e.g., Fornell, Rust, and Dekimpe 1996; Yeung et al. 2013). These insights, yet, are mostly limited to the aggregated economic level and therefore disregard attributes of the focal object of interest (e.g., stores or products). Individual level analyses are still more the exception than the rule.

One reason may be the absence of individual and longitudinal consumer satisfaction data. Survey-based measures, as often used in the general satisfaction literature, are normally limited to a relatively short time horizon. A direct measure of consumer satisfaction with a purchase, however, that is highly disaggregate, available for long time horizons, and easily obtainable may be seen in consumers' online opinion as represented in the numeric rating and review sentiment of online product reviews.

There is a fair amount of agreement among researchers, practitioners, and consumers that such online opinions are of particular relevance for both (potential) buyers and company performance. (Potential) buyers use online opinions regularly to learn about the quality of products (Zhao et al. 2013), ultimately striving to reduce uncertainty about the purchase by identifying products that best match their individual needs and usage conditions (Chen and Xie 2008). For firms on the other side, online opinions are important because they may impact sales (Chevalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010) and are regularly used by marketers to enrich their marketing strategies (Chen and Xie 2008; Cui, Lui, and Guo 2012).

Around 20% of consumers submit their own online opinion for the majority of their online purchases (Pilon 2016). Thereby, consumers inevitably communicate their own opinion regarding experienced product performance (De Langhe, Fernbach, and Lichtenstein 2016) and potentially resulting (dis-)satisfaction with their purchase. Prior research on online opinion formation, however, has demonstrated this outcome to not be a purely rational process. There is extensive evidence for different biases like temporal, sequential, and social dynamics that influence how consumers evaluate products they purchased (e.g., Godes and Silva 2012; Moe and Trusov 2011). Nevertheless, existing research in this domain has limited its scope on influences within an opinion platform's prevailing rating environment and reviewers' characteristics. Potential factors being exogenous to the focal platform have not been

considered so far.

At this point, our study combines both streams of research on business cycles in marketing and online opinion formation to contribute to both of them in a unique way. First, we address the lack of empirical evidence regarding an impact of macroeconomic changes on consumers' postpurchase behaviors in the business cycle literature. To do so, we incorporate online opinion as a direct representation of individual satisfaction with a purchase. Given the disaggregate nature of our data, we are also able to consider product characteristics as potentially moderating factors of the business cycle-online opinion relationship. Popular products increase consumers' awareness of and reduce their uncertainty about a purchase by providing more information through previous consumers' product evaluations. We therefore see product popularity as a viable characteristic that may amplify or attenuate the impact of business cycles on online opinion. Second, we extend research on online opinion formation by considering potential drivers of online opinions that are exogenous to the focal review platform, like the general state of the economy. Thereby, we acknowledge both numeric ratings and review sentiment being important measures of online opinion, something that has been widely neglected to date. In conclusion, we pursue the following two research objectives:

- Investigate how economic expansions and contractions impact numeric ratings and review sentiment in online product reviews.
- Determine the moderating role of product popularity in the business cycle-online opinion relationship.

To do so, we rely on an extensive data set containing book reviews from the online retailer Amazon.com with the earliest reviews dating back to 1996 and the latest to 2014. Amazon.com is the dominant e-commerce platform in the U.S., accounting for roughly one quarter of the online retail market (Hadad 2017), and one of the largest accumulations of online opinions on the Internet. The books category, furthermore, accounts for over 27% of the existing product

reviews at Amazon within the available time period, making it particularly relevant when investigating online opinion. Covering almost two decades, the longitudinal characteristics of this data further allow to capture the potential effects of multiple business cycles. We complement the review data with macroeconomic information from the National Bureau of Economic Research (NBER) and construct a semi-dummy variable to represent both different phases of a business cycle and their respective magnitudes. Our modeling approach considers three groups of factors influencing online opinion: (1) characteristics of the macroeconomic environment, (2) product characteristics, and (3) reviewer characteristics. Whereas the first group is derived from the literature on business cycles and is core to our research objectives, the other two groups of factors are obtained from the literature on online opinion formation. We apply ordinal logistic regressions and linear regressions to test the impact of macroeconomic conditions on both ordinal star ratings and continuous review sentiment retrieved from online product reviews.

Our results reveal that economic expansions and contractions have apparent and far-reaching effects on the numeric ratings and review sentiment in online product reviews. The numeric ratings are, on average, negatively affected by economic expansions. This negative impact is particularly driven by a decline in the probability for a focal product to receive another 5-star rating. As such, an expansion by 1% (2%, 3%) in macroeconomic performance reduces the probability to receive another 5-star rating by -.6pp (-1.2pp, -1.8pp). Correspondingly, the probability for a focal product to receive a 4-star rating instead shows the strongest increase. Thus, an economic expansion by 1% (2%, 3%) increases the probability for another 4-star rating by .3pp (.6pp, .8pp). As the mean rating across all products and reviews in our data sample is 4.25, receiving a 4- instead of 5-star rating brings, on average, a devaluation of the product. The review sentiment in online product reviews, however, is affected by both economic expansions in a negative and contractions in a positive way. The ability of review sentiment as a measure

of online opinion to capture both effects may be based on its continuous and more fine-grained nature compared to the ordinal rating measure. Therefore, these results underline the importance to consider alternative measures of online opinion that are capable to capture potentially weaker signals and shifts in online opinions. Previous studies have thereby predominantly relied on numerical ratings (e.g., Godes and Silva 2012; Moe and Trusov 2011; Wang, Menon, and Ranaweera 2018).

Furthermore, our findings indicate that product popularity may rather be a disadvantageous product characteristic when being faced with changing economic conditions. As such, the negative impact of economic expansions on online opinion appears to be much more severe for popular products. For instance, for a less popular product with only 20 reviews the probability to receive another 5-star rating remains basically unaffected with increasing economic expansion. Products with over 1000 reviews, however, show a reduction in the probability to receive another 5-star rating by -11.6pp (-23.0pp, -33.2pp) when the economy expands by 1% (2%, 3%). This tendency also exists for the sentiment in online product reviews. Additionally, product popularity has no significant effect on the relationship between economic downswings and review sentiment. Therefore, popular products loose with regard to their mean evaluation relative to less popular products during economic contractions but do not exhibit appropriate gains in the subsequent economic contraction. Thus, popular products are in a more disadvantageous position when it comes to dealing with changing economic conditions compared to less popular product. However, it should be noted that these results are limited to the potential effects on consumers' online opinion and do not account for potential effects product popularity may have on sales performance.

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Paper I

What Chatter Matters in Times of Economic Change?

The Impact of Consumer Confidence on eWOM Effectiveness

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Abstract

Electronic word of mouth (eWOM) serves as a valuable source of information for consumers when making purchase decisions online. Online product reviews, thereby, constitute an effective tool to learn about the quality of products, own preferences, and, ultimately, help to reduce the uncertainty about a purchase. Existing literature typically concentrates on the direct impact of online product reviews on sales. However, this relationship may change when economic conditions shift and, for instance, avoidance of purchase failure becomes more important. Therefore, the author investigates the moderating role of consumer confidence on the relationship between key eWOM metrics and sales. The empirical study is based on a unique and longitudinal product level data set, containing weekly sales-rank, price, and eWOM information from Amazon.com and economic data from the University of Michigan - Surveys of Consumers. Using a first-difference estimation approach, this study is the first to demonstrate the changing effectiveness of these eWOM characteristics for consumers' decision making process in the light of varying economic conditions.

Keywords: Electronic word of mouth, online product reviews, business cycles, consumer confidence

1 Introduction

Crisis-hit consumers tend to behave differently from those experiencing economic prosperity (Ang, Leone, and Kotler 2000; Dutt and Padmanabhan 2011). Current research does not only demonstrate existing sensitivity of spending in particular industries or categories (e.g., Deleersnyder et al. 2004) and the existence of distinct consumer strategies to cope with adverse economic conditions (e.g., Dutt and Padmanabhan 2011), but also indicates a changing effectiveness of marketing instruments such as advertising (Graham and Frankenberger 2011; Van Heerde et al. 2013) or pricing (Gordon, Goldfarb, and Li 2013; Van Heerde et al. 2013). However, while these latter studies have almost exclusively focused on company owned marketing instruments, other potentially important sources of information that are known as earned media (Stephen and Galak 2012) - such as electronic word of mouth (eWOM) - have been widely neglected.

This lack of attention is surprising given the prevalence and popularity of eWOM, particularly in consumers' prepurchase activities. Babić et al. (2016) define eWOM as the act of consumers to provide information about goods, services, brands, or companies to other consumers through the Internet. This information may be disseminated through various ways, e.g., blog posts, tweets, or product reviews and ratings on opinion platforms, to name a few. Importantly, potential buyers actively seek and trust such information for their decision making. Around 90% of consumers consult eWOM in form of online product reviews before visiting a business and 88% of consumers trust such eWOM sources as much as personal recommendations (Saleh 2015). Thus, eWOM constitutes an effective tool for consumers to learn about the quality of products (Zhao et al. 2013) or their own preferences (Wu et al. 2015), resulting in a reduction of uncertainty about the purchase by identifying products that best match their idiosyncratic usage conditions (Chen and Xie 2008). A fact that matters even more when overall spending is squeezed during tough economic times.

For firms on the other side, eWOM is relevant because it potentially may impact sales (Chevalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010) or be even used to enrich marketing strategy (Chen and Xie 2008; Cui, Lui, and Guo 2012). Indeed, marketers nowadays actively try to harness eWOM as a marketing tool and invite consumers to submit their product evaluations to respective opinion platforms (Dellarocas 2003). Knowledge about potential shifts in the effectiveness of eWOM due to changing economic conditions should accordingly be of great interest for marketers, for reaping benefits or avoiding potential downsides. During the Great Recession (2007 to 2009), for instance, Starbucks discovered its customers to be fatigued by premium priced coffee and to increasingly defect to cheaper but good-enough competitors. This erosion of loyalty has significantly been accelerated by the instantaneous spread of accompanying eWOM (Flatters and Willmott 2009). The goal of this study therefore is to pursue the following research objective:

- Investigate how changes of consumer confidence influence the effectiveness of eWOM valence, volume, and variance in driving sales.

We consider three metrics that have been identified by previous research to capture different aspects of eWOM: its volume (i.e., the total amount in eWOM interactions), valence (i.e., the positivity or negativity in eWOM interactions), and variance (i.e., the heterogeneity in eWOM interactions). We construct a unique and longitudinal data set on the product level, containing weekly sales-rank, price, and eWOM information from different sources, covering a total time span from 2010 to 2014 and two product categories. We investigate the impact of the economic environment by including consumer confidence as a moderating factor. To do so, we use the publically available Index of Consumer Sentiment (ICS) which is published by the University of Michigan - Survey of Consumers. Overall, we thus build an encompassing data set that combines behavioral measures with market data and aggregate economic information.

Our results reveal that the effectiveness of particular eWOM metrics in driving sales indeed varies conditional on consumer confidence. As such, improving economic conditions diminish the positive impact that eWOM volume and variance have on product sales performance. Importantly, these results are independent of potential price effects.

In the next section, we review relevant literature from the research streams on business cycles in marketing and eWOM effectiveness. After specifying our data bases and empirical estimations, we describe and discuss our results before concluding with managerial implications and directions for future research.

2 Literature Review

This study refers to two different streams of marketing research literature that have not been combined so far. First, we tie into work on the impact of business cycles on the effectiveness of marketing instruments. Second, we refer to literature on eWOM effectiveness.

2.1 Business Cycles and Marketing

Research on consumer-generated eWOM effectiveness over the course of changing economic conditions is scarce, if not non-existent. To date, there is only one study by Dhar and Weinberg (2016) that deviates from the usual focus on company-owned marketing instruments and considers the interplay of expert-generated eWOM and consumer confidence on box office attendance. Using U.S. data on the Index of Consumer Sentiment (ICS) as an economic indicator for consumer confidence, the authors investigate the moderating role of consumer confidence on the relationship between movie critics' ratings and box office attendance. The authors not only find that movie demand behaves counter-cyclical, but also show that the valence of professional critics' ratings has a more positive impact on movie demand during economic downturns than during upturns. This is the first and only systematic empirical study

to demonstrate such effects. Professional movie critics and ordinary consumers, however, base their evaluation judgements on different standards (Holbrook 1999). Therefore, these results are not generalizable over both expert- and consumer-generated eWOM. Further, the authors concentrate only on one eWOM characteristic, namely its valence. Even though eWOM valence has been identified to be an important driving force of product demand (e.g., Chevalier and Mayzlin 2006), other characteristics like eWOM volume (e.g., Duan, Gu, and Winston 2008) and variance (Sun 2012) have been shown to be relevant too. Therefore, we see the work by Dhar and Weinberg (2016) as an important first step in assessing the effectiveness of earned media over varying economic conditions. However, we point towards the missing consideration of consumer-generated eWOM effectiveness in particular.

Other studies that are considered related to our study rather focus on the effectiveness of company-owned marketing instruments such as pricing (Estelami, Lehmann, and Holden 2011; Gordon, Goldfarb, and Li 2013), investments in research and development (Srinivasan, Lilien, and Sridhar 2011; Steenkamp and Fang 2011), or advertising (Graham and Frankenberger 2011; Sethuraman, Tellis, and Briesch 2011; Srinivasan, Lilien, and Sridhar 2011; Steenkamp and Fang 2011; Tuli, Mukherjee, and Dekimpe 2012; Van Heerde et al. 2013).

While the knowledge on the effectiveness of pricing as a marketing instrument is quite conclusive, i.e., pricing decisions are more effective during economic downturns, the role of advertising remains subject to some disagreement. Moreover, studies in this research domain show quite some variation in their level of temporal aggregation and their approach to identify business cycle phases. Relying on yearly advertising expenditures, Graham and Frankenberger (2011), for instance, show that there are indeed differential effects of advertising on firms' current and future earnings across recessionary and non-recessionary times. For most companies, the recommended action is to increase rather than cut advertising expenditures in times of economic struggle. Srinivasan, Lilien, and Sridhar (2011) add that the effects of

advertising spending on profits and stock returns are determined by the company's market share, financial leverage, and product-market profile. However, most companies tend to overspend on advertising during recessions while they should instead focus more on, e.g., research and development investments. While both studies rely on a discrete classification of business cycle phases based on turning dates provided by the U.S. National Bureau of Economic Research (NBER) Business Cycle Dating Committee, later studies on advertising effectiveness infer the state of the economy through filtering approaches applied to official economic indicators. For instance, Steenkamp and Fang (2011) apply the Hodrick-Prescott (HP) low-pass filter (Hodrick and Prescott 1997) to annual real U.S. gross domestic product data (GDP) to construct a continuous and more fine-grained measure of deviations from the economy's long-term growth path. Hence, the authors show that increasing advertising share during economic contractions has a stronger effect on the company's profit and market share than increasing advertising share in expansions. Contrarily, Tuli, Mukherjee, and Dekimpe (2012), while constructing a discrete recession variable after applying the HP filtering approach, find no evidence of differential effects of stock-market reactions to unexpected changes in advertising spending across economic expansions and contractions. Finally, Van Heerde et al. (2013) show that although short-term advertising elasticities do not vary over economic phases, long-term advertising elasticities do indeed increase during economic expansions.

We seek to contribute to this line of research on two fronts. First, we extend the focus on alternative marketing activities other than the prevailing company-owned marketing instruments like pricing and advertising. Thereby, we take the approach of Dhar and Weinberg (2016) a step further. While their study provides the first systematic investigation of expert-generated eWOM effectiveness over varying economic conditions, our study is the first to consider consumer-generated eWOM effectiveness in the context of economic changes. The distinction between expert- and consumer-generated eWOM is particularly important, because

professional movie critics and ordinary consumers base their evaluation judgements on different standards (Holbrook 1999). This may lead to discrepancies in how professionals and consumers evaluate certain products and subsequently to different sales effects. Furthermore, Dhar and Weinberg (2016) consider valence as the only eWOM characteristic that may influence product demand. We, however, take a more comprehensive approach and examine the impact of eWOM valence, volume, and variance, all of which have been acknowledged in previous research to affect product demand and to represent different aspects of eWOM. Second, we deepen the insights on ICS as an indicator for economic performance. Compared to GDP-based indicators, the ICS captures consumers' subjective expectations not only towards the short- and long-term economic development, but also towards their own financial situation. Therefore, the ICS is capable of reflecting not only consumers' "ability to purchase" but also their "willingness" to do so (Katona 1968).

2.2 EWOM Effectiveness

Another stream of research we contribute to is that of eWOM and its ability to drive retail sales. The effectiveness of eWOM has attracted considerable academic interest in the past two decades. Although most research has come to the conclusion that eWOM has a significant monetary effect on sales over and above traditional marketing mix instruments (Chen, Wang, and Xie 2011; Chevalier and Mayzlin 2006; Moe and Trusov 2011), there still is considerable disagreement about which eWOM characteristics primarily drive this effect.

Although several studies have considered the potential effects of eWOM valence, volume, and variance on product performance, they show some inconsistent empirical results with regard to these three characteristics. Some studies document evidence that particularly the volume of eWOM is a strong predictor of product sales (e.g., Duan, Gu, and Winston 2008; Gu, Park, and Konana 2012; Ho-Dac, Carson, and Moore 2014; Liu 2006, Xiong and Bharadwaj

2014). Liu (2006), for instance, investigates the impact of both volume and valence of posted user reviews on weekly movie box office sales. Thereby, the author only finds the effect of eWOM volume to be significant. This result is supported by Duan, Gu, and Whinston (2008), who investigate the impact of eWOM volume and valence on daily movie box office sales for the first two weeks after release. Other studies also emphasize the significance of eWOM valence as relevant predictor of product performance (e.g., Chevalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010; Dellarocas, Zhang, and Awad 2007). Dellarocas, Zhang, and Awad (2007), for instance, find both eWOM volume and valence to have a significant effect on weekly movie box office sales growth. Similarly, Chevalier and Mayzlin (2006) find eWOM volume and valence to have significant effects on the sales performance of books. Lastly, other studies report significant effects of eWOM variance (e.g., Clemons, Gao, and Hitt 2006; Sun 2012). Clemons, Gao, and Hitt (2006) find that the valence and variance, but not the volume, of ratings have an impact on sales growth in the craft beer category. Sun (2012), concentrating on the informational role of eWOM variance for potential buyers, finds a higher standard deviation of ratings on Amazon to improve a book's relative sales rank only when the average rating is low.

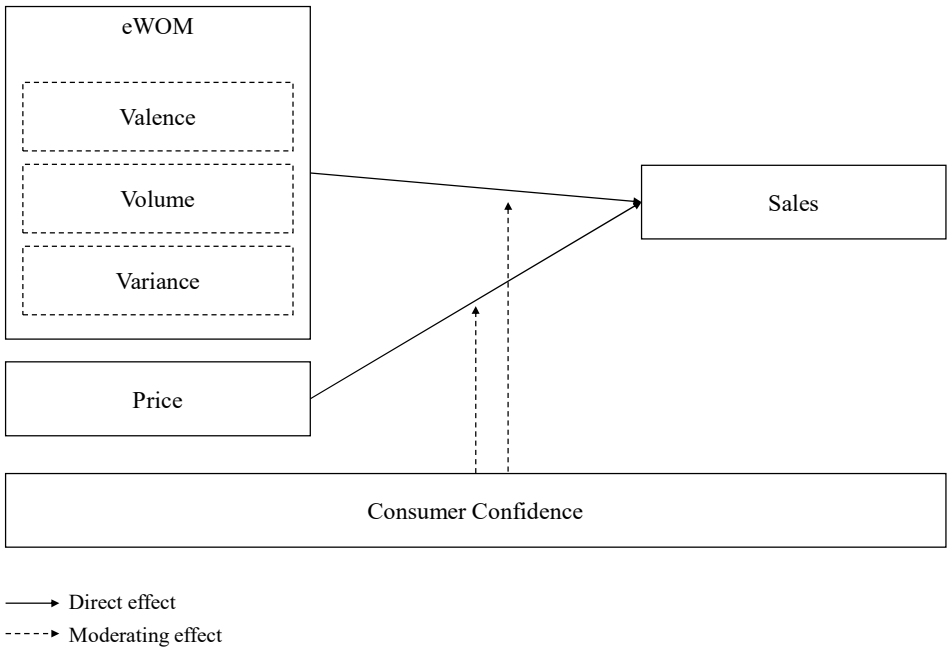
We contribute to this stream of research in two ways. First, while previous studies in this regard have taken a rather local perspective and limited their focus almost exclusively on sales drivers that are related to the product environment (i.e., different eWOM metrics, retailer pricing), we extend this work and establish consumer confidence to be an important global influencing factor that is exogenous to retailers and consumers alike. More importantly, we establish consumer confidence to be a relevant moderator of eWOM effectiveness. Second, while previous studies have utilized data samples with cross-sectional characteristics or samples comprising rather short time spans of one or two years (e.g., Chevalier and Mayzlin 2006; Duan,

Gu, and Winston 2008; Liu 2006), we leverage the longitudinal properties of a data set with a much longer time frame.

3 Conceptual Framework

Our study focuses on the moderating role of consumer confidence on eWOM effectiveness with regard to driving sales. Therefore, we propose a conceptual framework that combines potential influencing factors derived from both the literature on business cycles in marketing and from the literature on eWOM effectiveness. Specifically, we consider (1) three key eWOM characteristics (volume, valence and variance), (2) product price as a cost-related factor, and (3) consumer confidence representing consumers' perceptions of the general and their personal economic situation. Figure 1 gives an overview of our proposed conceptual framework.

Figure 1: Conceptual Framework



Prior studies have already established that economic conditions affect consumers' ability and willingness to spend. Some studies, for instance, have used the ICS as a proxy for consumer confidence and linked it to consumers' overall spending (e.g., Allenby, Jen, and Leon 1996; Dhar and Weinberg 2016; Fornell, Rust and Dekimpe 2010; Ludvigson 2004). The direction of the impact, however, seems to be strongly dependent on the focal product category. While, e.g., durables (Ludvigson 2004) and fashion products (Allenby, Jen, and Leon 1996) seem to be positively associated with positive consumer confidence, movie attendance decreases (Dhar and Weinberg 2016). We expect demand in our focal categories of books as well as toys and games to be rather counter-cyclical too and thus to be more important when the economy turns sour. Both product categories constitute relatively cheap forms of entertainment and thus may be an attractive alternative to more expensive forms of amusement during tough economic times. With unemployment on the rise and declining working hours, people may unintentionally spent more time at home and feel the urge to escape a depressing reality into more pleasing worlds (Pfanner 2009). Moreover, when overall spending is squeezed, parents may want to ensure that children do not lose out and still enjoy (Thompson 2012).

However, when economic conditions deteriorate and disposable income is shrinking, making the right purchase decisions becomes even more of a necessity. Thus, gathering information and reducing potential uncertainties before a purchase increases in importance, even for less expensive products. EWOM provides potential buyers unprecedented access to product information. Prior studies have shown how eWOM information are leveraged by consumers' in the prepurchase phase to learn more about the quality of products (Zhao et al. 2013) or their own preferences (Wu et al. 2015). Thereby, consumers seek to reduce the uncertainty about a purchase by identifying products that best match their idiosyncratic usage conditions (Chen and Xie 2008). Therefore, it may be assumed that eWOM becomes more

effective during tough economic times, when consequences of purchase failure are relatively higher. Empirical evidence for consumer-related eWOM, however, does not exist to date. Furthermore, the question remains whether different underlying aspects or characteristics of eWOM likewise increase in importance during economic downturns (or decrease during economic upturns).

The literature on eWOM distinguishes between three key aspects or characteristics of eWOM: its volume, valence, and variance. The volume of eWOM measures the "total amount of eWOM interaction" (Liu 2006, p.75) and is an indicator of how many people used or experienced a certain product. It can increase the popularity of and consumers' awareness towards this product and thereby have an impact on sales performance (Chen, Wang, and Xie 2011; Park, Gu and Lee 2012). The rationality behind this effect lies in the bandwagon effect (e.g., Van den Bulte and Lilien 2001), in which the mere existence of other buyers' experience with a product gives a signal of risk reduction in the present decision making process. We would expect eWOM volume to be more important during economic downturns than upturns. Furthermore, eWOM valence represents "the idea that eWOM can be either positive, negative, or neutral" (Liu 2006, p. 75). It is an indicator for a product's reputation and expected product quality (Liu 2006) and thereby may have an impact on sales performance (Chevalier and Mayzlin 2006). Whether eWOM valence is more effective during tough economic times, however, is not that straightforward to answer. It may increase in effectiveness as consumers want to make sure that their limited disposable income is well spent on products of high quality. Yet business cycle research has shown that consumers become more price (rather than quality) sensitive when the economy goes down (Gordon, Goldfarb, and Li 2013; Lamey et al. 2012; Van Heerde et al. 2013). To account for such competing price effects, we include product price as a control variable in our empirical analysis. Similar ambiguity, however, remains with regard to the aspect of eWOM variance, which represents the "heterogeneity in consumer opinions"

(Sun 2012, p. 697). High variance is characteristic for niche products that people either like or dislike. Low variance, contrarily, signals consumers' agreement about a product, which may be either good or bad and therefore lead to either a positive or negative impact on sales (Babić et al. 2016). One could argue that because consumers are more risk averse during tough economic times, a higher variance - representing inconsistent opinions - should have a negative impact on sales. Contrarily, consumers may feel better informed about all advantages and disadvantages of a product based on more diverse opinions about it, which may even reduce the risk of a mismatch.

4 Methodology

4.1 Research Context and Data

Our empirical analysis uses sales-rank, price, and product review information from the online retailer Amazon.com. Accounting for roughly one quarter of the online retail market, it is the dominant e-commerce platform in the U.S. (Hadad 2017). However, historic data on sales-ranks and prices in particular are not easily obtainable as Amazon.com does not store such information itself to make it readily available. Therefore, this issue has been side stepped by using a web-crawler to collect data from several price and sales-rank tracking websites in graph form.[1] These websites rely on real-time data directly obtained from Amazon.com and make it publically available as a time series graph.[2] These graphs have been analyzed with an algorithm pixel-by-pixel to retrieve the underlying data points regarding prices and sales-ranks. Due to heterogeneous sampling intervals in the graph data, the price and sales-rank information have been averaged to a weekly level. Importantly, each product can uniquely be identified based on its Amazon Standard Identification Number (asin). The raw data set is composed of over 20,000

[1] We are grateful to Jörn Boehnke (Center of Mathematical Sciences and Applications, Harvard University) and Brock Mendel for collecting and providing the data.
[2] Graphs were collected from the 3-rd party tracking websites www.camelcamelcamel.com, www.ipricetracker.com, www.keepa.com, www.pricezombie.com, and www.thetracktor.com.

products from the categories books as well as toys and games, covering a total time span from 2010 to 2014. Unfortunately, unpopulated information with regard to sales-ranks and prices per product are quite common. Price information, for instance, are missing when products have been offered only by third-party sellers. Sales-rank information are not available in cases where products have been out of stock. To be able to use a first-difference estimation approach, as described in the following sections, we filtered out all products with complete information on sales-ranks and prices. This filtering procedure has left us with complete information on 511 products.[3]

Furthermore, we rely on an extensive data set containing online product reviews from Amazon.com which is made available through the Stanford Network Analytics Project (He and McAuley 2016). The review data set covers over 82 million individual product reviews across multiple product categories and spans a time frame from 1996 to 2014. For each review, there is information available regarding the unique product (asin) and reviewer identifier, the star rating, the review text (including a review summary), the product category, and the date of posting. We filtered out all reviews for products that are in our sales-rank and price sample based on the unique asin identifier.

Finally, publically available data on the monthly Index of Consumer Sentiment (ICS) provided by the University of Michigan[4] is used as a measure of consumers' perceptions of the overall economic environment.

[3] We test for systematic differences of the filtered and remaining product samples by comparing means of the first-difference operators of sales-rank and price. We do not find any statistically significant differences for these variables across samples. Thus, we assume products with complete transaction information to be not systematically different from products with incomplete information.
[4] Data and more information are available at the University of Michigan - Survey of Consumers website: http://www.sca.isr.umich.edu/

4.2 Measures

Dependent measures. Several prior studies have used Amazon sales-rank (SALESRANK) data as a measure of product sales (e.g., Archak, et al. 2011; Chevalier and Mayzlin 2006; Sun 2012). The properties of sales-rank data as a proxy for product sales have been established and extensively discussed by Chevalier and Goolsbee (2003). We follow the prevalent approach in existing literature and perform our estimation directly on the sales-rank as a proxy for product demand. The sales-rank information are aggregated at the weekly level.

Independent measures. To measure the underlying state of the economy, we rely on the monthly Index of Consumer Sentiment (ICS) that is published by the University of Michigan. Using the ICS as an indicator of consumers' perceptions of the economic environment has been established in several studies (Carrol, Fuhrer, and Wilcox 1994; Howrey 2001; Ludvigson 2004). Compared to approaches where the state of the economy is inferred from continuous economic indicators such as the GDP, the ICS captures consumers' subjective expectations not only towards the short- and long-term economic development but also their own financial situations. Therefore, the ICS reflects not only consumers' "ability to purchase" but also their "willingness" to do so (Katona 1968). The data for constructing the ICS is collected throughout and published at the end of each month. To meet the weekly aggregation level of our Amazon sales-rank and price data, we transform the monthly series to a weekly level through linear interpolation.[5]

The existing literature has measured and operationalized eWOM in multiple ways to capture its different underlying aspects and characteristics. Most studies distinguish between three key metrics: volume, valence, and variance. EWOM volume (VOL) measures the "total amount of eWOM interaction" (Liu 2006, p.75). Because eWOM volume is an indicator of how many people used or experienced a certain product, it can increase the popularity of and

[5] For a similar approach based on quarterly GDP data, see Van Herde et al. 2013.

consumers' awareness towards this product and thereby may increase sales performance (Chen, Wang, and Xie 2011; Park, Gu and Lee 2012). We operationalize eWOM volume as the cumulative number of reviews of product i at time t. Furthermore, eWOM valence (VAL) captures the sentiment or polarity expressed in consumers' product evaluations and represents "the idea that eWOM can be either positive, negative, or neutral (Liu 2006, p. 75). The valence of eWOM is indicative for a products reputation and expected product quality (Liu 2006) and thereby may have an impact on sales performance (Chevalier and Mayzlin 2006). We measure eWOM valence as the cumulative mean rating of product i at time t. Finally, eWOM variance (VAR) represents the "heterogeneity in consumer opinions" (Sun 2012, p. 697). High variance is characteristic for niche products that people either like or dislike. Low variance, contrarily, signals consumers' agreement about that product. However, consumers may agree that the product is either good or bad which can lead to either a positive or negative impact on sales (Babić et al. 2016). We operationalize eWOM variance as the cumulative variance of review ratings of product i at time t.

We further consider Amazon product prices (PRICE) denoted in U.S. dollar cents in our analysis. The historical product prices are, in a similar way as the corresponding sales-rank information for a product, retrieved from price graphs provided by third party tracking websites. Prices represent weighted weekly averages. Table 1 provides descriptive statistics and correlations for all variables used in our model.

Table 1: Descriptives and Correlation Matrix

		N	M	SD	Min	Max	1	2	3	4	5
1	SALESRANK	15081	277238	372790	1.00	3520312					
2	ICS	15081	80.88	2.89	56.33	85.10	**.11**				
3	VAL	15081	4.32	.65	1.00	5.00	**.03**	**.07**			
4	VOL	15081	52.54	261.64	1.00	3501	**-.12**	-.01	**.04**		
5	VAR	13627	.99	1.06	.00	8.00	.01	**-.05**	**-.68**	**-.02**	
6	PRICE	15081	2371	4233.21	99	34995	**-.08**	**-.04**	**-.14**	**-.04**	**.13**

Notes: M = mean; SD = standard deviation; Min = minimum; Max = maximum.
Bold figures indicate significance at $p < .01$.
Correlations based on untransformed variables.

4.3 Empirical Model

Prior studies find that eWOM is both driver and outcome of retail sales (Duan, Gu, and Whinston 2008; Godes and Mayzlin 2004). This relationship may raise concerns about potential endogeneity issues. Furthermore, there may be unobserved product characteristics or demand shocks that could influence retail sales, eWOM, and prices altogether. We address this issue by estimating a first-difference econometric model that is capable of controlling for potential endogeneity (Wooldridge 2002). Controlling for endogeneity with a first-difference approach is the most frequent endogeneity correction in the eWOM marketing literature (Babić et al. 2016). Thereby, differencing is performed either across platforms (Sun 2012), across time (Chen, Wang, and Xie 2011), or both (Chevalier and Mayzlin 2006). As our research context is focusing on a single platform, we leverage the longitudinal characteristics of our data sample and specify the first-difference operators across time. We thus specify our model as follows:

$$
\begin{aligned}
(1) \quad -\Delta \ln Salesrank_{it+1} = {} & \beta_1 \Delta ICS_{t-1} + \beta_2 \Delta VAL_{it} + \beta_3 \Delta \ln VOL_{it} + \beta_4 \Delta VAR_{it} + \beta_5 \Delta \ln PRICE_{it} \\
& + \beta_6 \Delta VAL_{it} \Delta ICS_{t-1} + \beta_7 \Delta \ln VOL_{it} \Delta ICS_{t-1} + \beta_8 \Delta VAR_{it} \Delta ICS_{t-1} \\
& + \beta_9 \Delta \ln PRICE_{it+1} \Delta ICS_{t-1} + \Delta \varepsilon_{it}
\end{aligned}
$$

where Δ is the first-difference operator over time of a particular variable ($\Delta X_t = X_t - X_{t-1}$), ln represents the natural logarithm, and ε_{it} the idiosyncratic error term for product i at time t. Similar to previous research (Gu, Park, and Konana 2012), we use inverted SALESRANK values as a sales measure to make the results more intuitive, because higher sales-rank values correspond with lower sales. We also use a log-transformed dependent measure which is consistent with prior literature that examines the relationship between eWOM and sales (Chevalier and Mayzlin 2006). Additionally, we also specify our dependent variable with a time lead of one period (t+1) to account for the fact that changes in eWOM may impact future sales rather than sales in the same period (Hu et al. 2012). Similarly, we specify our economic

indicator variable ICS with a time lag of one period (t-1) to account for its lagging nature (Carroll, Fuhrer, and Wilcox 1994). VOL is log-transformed to account for diminishing marginal effects of the number of reviews (Chevalier and Mayzlin 2006). VAL and VAR represent the valence and variance of eWOM respectively.

4.4 Results

We use R (R Core Team 2018) in version 3.5.1 and the package plm (Croissant and Millo 2018) in version 2.0-1 for model estimation. Table 2 summarizes the results of our estimation process.[6]

Table 2: Estimation Results

DV	$\Delta lnSALESRANK_{it+1}$	
IV	*Coef.*	*SE*
ΔICS_{t-1}	.107	.113
ΔVAL_{it}	3.542***	1.281
$\Delta lnVOL_{it}$	-.002	.492
ΔVAR_{it}	1.520*	.798
$\Delta lnPRICE_{it+1}$	-1.666**	.833
$\Delta VAL_{it}*\Delta ICS_{t-1}$	-.044***	.016
$\Delta lnVOL_{it}*\Delta ICS_{t-1}$	-.002	.006
$\Delta VAR_{it}*\Delta ICS_{t-1}$	-.018*	.010
$\Delta lnPRICE_{it+1}*\Delta ICS_{t-1}$	.012	.010
Product fixed effects	Included	
Time fixed effects	Included	
Adjusted R-square[7]	.004	
Model fit F	6.096***	
N	12401	

Notes: DV = dependent variable; IV = independent variable; N = number of observations; Δ = first-difference operator; ln = natural logarithm; Coef = estimated coefficient; SE = standard error.
*$p < .1$; **$p < .05$; ***$p < .01$.

[6] To test for multicollinearity, we calculated variance inflation factors (VIFs). The VIFs for all independent variables are well below the recommended cut-off of 10 (Hair et al. 1995).
[7] Note that models in first differences generally exhibit lower model fit criteria than models in levels. Previous studies relying on differencing document comparable model fit values as in this study (e.g., Chevalier and Mayzlin 2006).

The positive and significant parameter estimate of VAL indicates that an increase in the cumulative average review rating has a positive impact on incremental sales ($\beta_2 = 3.542$, $p < .01$). Additionally, the positive and significant parameter estimate of VAR implies that increases in the cumulative variance of review ratings drive incremental sales too. Contrarily, the negative and significant parameter estimate of PRICE shows that price increases are negatively correlated with incremental sales ($\beta_5 = -1.666$, $p < .05$). These results are consistent with previous research (e.g., Gu, Tang, and Winston 2013; Sun 2012). The parameter estimates of VOL ($\beta_3 = -.002$, $p \geq .1$) and ICS ($\beta_1 = .107$, $p \geq .1$) yet show no significant effects. Our key interest, however, lies in the question whether eWOM differs with consumer confidence. The parameter estimate of the interaction VAL*ICS reveals that the positive impact of eWOM valence on incremental sales diminishes with improvements of consumer confidence ($\beta_6 = -.044$, $p < .01$). The same is true for the parameter estimate of VAR*ICS, which shows that the positive impact of eWOM variance also diminishes with improvements of consumer confidence ($\beta_8 = -.018$, $p < .1$). No significant effects were found for the interactions VOL*ICS ($\beta_3 = -.002$, $p \geq .1$) and PRICE*ICS ($\beta_3 = -.013$, $p \geq .1$).

5 Discussion and Summary

We discuss our findings with regard to our research question stated at the beginning and clarify how answering this question contributes to existing literature on business cycles in marketing and eWOM effectiveness. In addition, we specify some important implications for marketers to offer concrete managerial action recommendations. Lastly, we point out some prevalent limitations of this study that may provide a fruitful avenue for future research.

5.1 Discussion

The key objective of this study is to investigate how changes of consumer confidence influence the effectiveness of eWOM valence, volume, and variance in driving sales. To do so, we base our analysis on a unique data set comprising weekly sales-rank, price, and eWOM information on the product level from Amazon.com, which covers a time span from 2010 to 2014. We complement this data with information on the publically available Index of Consumer Sentiment as a measure of consumers' perceptions of prevailing economic conditions. Thereby, we are able to build an encompassing data set that combines behavioral measures with market data and aggregate economic information.

By including eWOM volume, valence, and variance as potential influencing factors, we acknowledge different aspects and characteristics of eWOM that have received considerable attention in previous studies. While eWOM volume is an indicator for the "total amount of eWOM interaction" (Liu 2006, p.75), eWOM valence represents "the idea that eWOM can be either positive, negative, or neutral (Liu 2006, p. 75). Finally, eWOM variance indicates the extent of "heterogeneity in consumer opinions" (Sun 2012, p. 697). Our results reveal that increasing eWOM valence and variance have positive effects on incremental sales, while increasing eWOM volume shows no significant effect. Importantly, the effectiveness of eWOM valence and variance in driving incremental sales indeed varies conditional on changes of consumer confidence. Concretely, improving economic conditions, as represented by an increase in consumer confidence, diminish the positive impact of eWOM valence and variance on incremental product sales. Thus, increasing eWOM valence and variance are more effective when the economy turns sour. Importantly, while controlling for potential product price changes, these results are independent of any price effects. Moreover, while price increases exhibit a negative impact on incremental sales, this effect, however, is neither attenuated nor amplified by changing economic conditions. Therefore, eWOM value and variance may be

considered more effective marketing instruments in driving sales performance during economic downturns than pricing.

In contrast to existing business cycle literature, that has demonstrated consumers to be rather price oriented when the economy goes down (Gordon, Goldfarb, and Li 2013; Lamey et al. 2012; Van Heerde et al. 2013), our results show that product quality, as indicated by eWOM valence, indeed is of greater importance for consumers' purchase decisions during economic downturns compared to upturns. This effect may be driven by consumers' effort to spend their limited disposable income on products that are perceived to be worth the money. When purchase failure is more costly during economic downturns, products that exhibit an increase in eWOM valence may reduce the perceived purchase risk, eventually driving incremental sales.

At the same time, consumers also value products that show an increase in eWOM variance and, thus, exhibit increasing heterogeneity in other consumers' opinions. Low variance signals consumers' agreement about a product being either good or bad (Babić et al. 2016). An increase in variance, however, implies a more diverse set of opinions. For prospective consumers this can also be more persuasive because it provides more information about advantages and disadvantages of a certain product, allowing to decide whether any of the negatively rated product attributes may prevent a purchase. Thus, even an increasing eWOM variance due to incoming negative evaluations may increase the information value of a product, reducing the risk of purchase failure, and therefore drive incremental sales.

5.2 Managerial Implications

Our results highlight how the effectiveness of eWOM in driving sales performance changes with consumer confidence, which bear important implications for retailers and manufacturers. Although both have little control over the current state of the economy,

knowledge about likely changes in eWOM effectiveness allows them to induce appropriate marketing actions.

Marketers nowadays actively harness eWOM as a marketing tool and invite consumers to submit their product evaluations to respective opinion platforms (Dellarocas 2003). Many retailers offer specific product tester programs, encouraging consumers to write reviews about a product by offering discounts or free product samples (e.g., Amazon Vine). While these programs are well-suited to drive the overall number of reviews, they do not necessarily lead to an increase in eWOM valence or variance. As our findings imply, the latter two characteristics do have a positive effect, which is even amplified during economic downturns. Thus, eWOM in general can be considered an attractive means for counter-cyclical marketing activities. Based on our results, the recommended action would be to bolster up such activities when the economy goes down. However, eWOM volume has shown no significant effect. Therefore, marketers should set an increased focus on gaining rather fewer, but more valuable (i.e., better or contrasting) product reviews to increase sales performance. Particularly those products outside the top rankings and with consistently lower ratings exhibit the largest potential for significant sales gains. That is, when positive eWOM not only increases the mean rating of a product in a substantial way but also the variance among existing ratings. In this case, marketers considering eWOM campaigns need to make sure that product testers are well targeted to submit positive reviews.

Furthermore, our results indicate that price changes are not more effective during economic downturns than upturns. Thus, price reductions do not lead to incremental sales, implying a shift of marketing budgets in favor of eWOM campaigns as recommended rather than price promotions. Additionally, eWOM activities bear the potential to have long-term effects that carry over to subsequent periods of economic prosperity, whereas price promotions are in general rather short-term oriented.

5.3 Limitations

Our study is subject to some limitations that promise fruitful avenues for future research. One limitation relates to the selection of books as well as toys and games as the focal context of research. Both categories can be considered as small luxuries that may gain in popularity during tough economic times. Future research, therefore, should consider other categories of, e.g., rather utilitarian nature in which the effectiveness of eWOM may follow diverging mechanisms. In such categories, pricing may play a more important role and thus undermine the effectiveness of eWOM characteristics. Furthermore, although the time span of our data set (2010 to 2014) is quite substantial when compared to existing eWOM literature, business cycle literature regularly relies on data which is available over longer periods of time. Since business cycles typically last between 1.5 and 8 years (Christiano and Fitzgerald 1998), longer time spans are needed to ensure multiple cycles are captured. The issue of course is one of mere data availability. However, the emergence of alternative data collection procedures, as described in data section, may provide future opportunities to tackle this issue.

References Paper I

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Paper II

Shifts Beneath the Surface: How Micro- and Macroeconomic Conditions Affect FMCG Shopping Strategies

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Abstract

Economic conditions, at individual micro- or national macroeconomic levels, substantially influence households' various shopping preferences. However, these shifts in households' preferences mainly have been analyzed in isolation and with an aggregate perspective. In this study, the authors combine comprehensive household-level transaction data with household-level income information and national economic indicators to identifying holistic shopping strategies, based on households' preferences for brand types, store formats, and price tiers. Establishing and characterizing seven distinct shopping strategies based on a hidden Markov model specification, they shed new light on how households switch among shopping strategies to cope with changing micro- and macroeconomic conditions. Notably, the influences of macroeconomic expansions and contractions are not mirror images, nor are households' switching patterns universal, such that substantial and varied shifts arise in the customer bases of supermarkets, discounters, and brand manufacturers. For these market actors, it is critical to realize whether households adjust their shopping strategies, and if so, which strategies they are abandoning and which ones they are adopting.

Keywords: Business cycle, income shocks, shopping strategies, FMCG

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1 Introduction

Households make nearly daily purchases, yet the conditions under which they make purchases change constantly. These changing conditions might take place on a personal, microeconomic level, such as if the main breadwinner receives a pay raise, the size of the household changes, or a household member loses a job; they also might reflect the macroeconomic business cycle with its reoccurring expansions and contractions, as recently highlighted by the Great Recession or the European debt crisis. These changing micro- and macroeconomic conditions substantially affect household spending and, in turn, companies' profits. *The Economist* (2011) estimated that the Great Recession led to an 8%, or $4,000, decrease in real annual spending among U.S. households, which amounts to $500 billion in foregone revenues. While households tend to postpone purchases of durable goods to times of economic prosperity (Deleersnyder et al. 2004; Dutt and Padmanabhan 2011), for fast moving consumer goods (FMCGs) deferring purchases often is not viable. Consequently, households must find ways to economize on the prices they pay (Dekimpe and Deleersnyder 2017).

Prior research identifies three shopping preferences that households adjust when faced with conditions that require them to reduce spending: They adjust their brand type preference by switching from national brands (NBs) to cheaper brands or private labels (PLs) (Cha et al. 2015; Dubé, Hitsch, and Rossi 2018; Lamey et al. 2007; Ma et al. 2011), their store format preference by switching from supermarkets to less expensive discounters (Cha et al. 2015; Lamey 2014; Ma et al. 2011), and their price tier preference by switching from regular to promotional prices (Cha et al. 2015; Ma et al. 2011). In detailing how households react to changing macro- and microeconomic conditions at large, this literature stream has "taken a fairly aggregate view" (Dekimpe and Deleersnyder 2017, p. 7) on households and their adjustments. For example, Dubé, Hitsch, and Rossi (2018) find that households increase PL

purchases during recessions, but we do not know whether all households do so or if differences exist across households in terms of which shopping preferences they adjust.

For regular FMCG shopping, each household may exhibit a different combination of shopping preferences for brand types, store formats, and price tiers: Perhaps the Middlebrow family primarily shops for NBs on promotion in supermarkets, but Mr. Doe prefers PLs in supermarkets, even as Mr. and Mrs. Everyman purchase NBs primarily from discounters. These distinct combinations of shopping preferences constitute what we define as *shopping strategies*. To implement these widely varying shopping strategies, households also undertake vastly different adjustments to realize savings when macro- or microeconomic conditions change. The Middlebrow family thus might retain its store format preference for supermarkets but adjust its brand type preference and purchase more PLs. Mr. Doe cannot make a similar adjustment; he already purchases mostly PLs in supermarkets. Instead, he might adjust his store format preference and increasingly shop in discounters. These idiosyncratic adjustments constitute switches from one shopping strategy into another. Yet even households with the same initial shopping strategy could realize savings through different means. For example, a household that uses the same initial shopping strategy as the Middlebrow family might react to deteriorating conditions by adjusting its store format instead of its brand type preferences.

For manufacturers and retailers, this vast variety of possible adjustments means that when macro- and microeconomic conditions change, the resulting complex transformations of their customer bases are difficult to detect. A supermarket patronized by both the Middlebrow family (switches to purchasing more PLs) and Mr. Doe (switches to discounters) might experience little change in its PL market share on aggregate, even though the composition of its customer base has changed substantially. Taking the firm's perspective, it is therefore not only critical to know whether households adjust their shopping strategy but also which previous strategy they are coming from and which they are switching to. Ignoring such contingencies

and changes to the customer base may result in an ineffective marketing mix and loss of market share in the long run.

To identify these various shifts that take place beneath the surface, as caused by changing macro- and microeconomic conditions, we pursue three foundational research objectives:

- Identify and characterize distinct shopping strategies based on households' brand type, store format, and price tier preferences.
- Investigate how households switch among shopping strategies, i.e., which strategies they are abandoning and which ones they are adopting, as a result of changing micro- and macroeconomic conditions.
- Determine the sensitivity of each shopping strategy to changes in micro- and macroeconomic conditions.

For these purposes, we employ a hidden Markov model (HMM) to model households' shopping preferences over time and thereby derive hidden states. Each hidden state reflects a distinct combination of shopping preferences that constitutes a shopping strategy. We base the analysis on a unique, comprehensive data set tailored to our research context. Using the GfK Germany ConsumerScan panel, we observe detailed information on each household's daily FMCG transactions. With its market-wide coverage, this data set provides details about various marketing mix elements, such as price, promotional activities, and assortment. Annual surveys of the households in the panel indicate demographics and each household's microeconomic conditions. We also gather macroeconomic data from the German Federal Statistical Office. Finally, we enrich our data set with advertising data from the Nielsen Company to control for advertising activities by all manufacturers and retailers in our sample.

The results reveal seven shopping strategies, each reflecting distinct shopping preferences. Households switch among shopping strategies in response to changes in micro- or macroeconomic conditions. Depending on a household's prior shopping strategy, it adopts

certain adjustments, though households with the same initial shopping strategy also may pursue different adjustments with contrary effects on shopping preferences; these specific effects would remain hidden beneath the surface in an aggregate analysis. For example, reduced household income leads some households to adopt a shopping strategy in which they spend more at supermarkets, while others spend more at discounters. Notably, households make adjustments during adverse macroeconomic conditions even if they suffer no income losses. On a more practical level, households exhibit strong preferences for NBs even when microeconomic conditions worsen and adjust by purchasing more NBs from discounters or on promotion. Furthermore, purchasing NBs in supermarkets represents a ceiling strategy across households that they adopt when microeconomic conditions improve. However, we do not observe a mirror effect of PL purchases in discounters when conditions worsen; some households remain reluctant to purchase PLs from discounters even in poor conditions.

In the next section, we review relevant literature, which informs the conceptual framework that underlies our empirical analysis. After specifying our data bases and model formulations, we describe and discuss our results in the order of our research objectives. We conclude with managerial implications for the FMCG retailing landscape and directions for future research.

2 Literature Review

Our study ties into business cycle research in marketing that shows that PL market shares (Lamey et al. 2007) and discounter market shares (Lamey 2014) increase during recessions, and that some of this effect carries over into subsequent expansion periods. Complementing results based on aggregate data, Dubé, Hitsch, and Rossi (2018) use household-level data and confirm prior findings (Lamey et al. 2007) by showing that households' income reduction during the Great Recession relates positively to their PL share of wallet (SOW),

though with substantially smaller short- and long-term effects. Ma et al. (2011) use gasoline prices to operationalize changing macroeconomic conditions and consider multiple shopping preferences, in terms of brand, store format, and price tier switching. They also include households' shopping frequency and purchase volume. Cha et al. (2015) identify adjustments that households employed to reduce their spending during the Great Recession, such as switching to cheaper store formats, cheaper brands, and products on price promotion. Moreover, a related research stream seeks to create typologies of households' adjustments to changes in macroeconomic conditions (Hampson and McGoldrick 2013; Quelch and Jocz 2009; Shama 1981). As we summarize in Table 1, we seek to contribute to this line of research on several fronts.

Table 1: Literature Overview and Contributions

Author(s)	Multiple shopping preferences	Interdependence of shopping preferences	Heterogeneity in adjustments	External validity (longitudinal field data)
Shama 1981	(✓)		✓	
Lamey et al. 2007				✓
Quelch and Jocz 2009	(✓)		✓	
Ma et al. 2011	✓			✓
Hampson and McGoldrick 2013	(✓)		✓	
Lamey 2014				✓
Cha et al. 2015	✓			✓
Dubé, Hitsch, and Rossi 2018				✓
This paper	✓	✓	✓	✓

First, we identify distinct shopping strategies, derived from multiple shopping preferences. Most studies cite isolated shopping preferences, such as for brand type (Dubé, Hitsch, and Rossi 2018; Lamey et al. 2007) or store format (Lamey 2014). Even in studies that analyze multiple shopping preferences, their interdependencies remain unaccounted for (Cha et al. 2015; Ma et al. 2011), such that simultaneous considerations of multiple shopping

preferences are lacking. Yet each household may purchase FMCGs using different combinations of shopping preferences and adjust different shopping preferences when conditions change. Therefore, it is important to observe multiple shopping preferences to identify *if* and *how* households adjust. In addition, individual shopping preferences likely are interdependent (Dekimpe and Deleersnyder 2017; Dekimpe et al. 2011; Lamey 2014; Ma et al. 2011); for example, discounters usually carry substantially more PLs than other store formats, so a household's preference for discounters almost inevitably leads to increased PL SOW too (Dekimpe and Deleersnyder 2017; Dekimpe et al. 2011; Lamey 2014). Failing to account for these interdependencies would overestimate the effect of changing conditions on, say, PL consumption, because part of it should be attributed to increased shopping at discounters. Therefore, we analyze multiple shopping preferences simultaneously while also controlling for their interdependencies and thus offer a novel way to draw a holistic picture of each household's shopping strategies and adjustments when faced with changing conditions.

Second, we identify different adjustments due to changing conditions, to build on prior studies that analyze households' reactions with a bird's-eye perspective (Dekimpe and Deleersnyder 2017). Each household may adjust different shopping preferences to realize savings, depending on its initial shopping strategy, and even households with similar initial shopping strategies may react differently. Unobservable, household-specific factors (e.g., brand and store loyalty, quality consciousness) influence how households react to a shift in conditions. For example, if the quality of food products is important to a particular household, it might not change its shopping behavior as much as households with less pronounced quality consciousness motives. Households with strong brand loyalty likely prefer to switch store formats; households with low brand loyalty might keep purchasing in the same store but switch to PLs. We uncover this variety in households' reactions to changing micro- and macroeconomic conditions, answering calls for research by multiple authors (Cha et al. 2015;

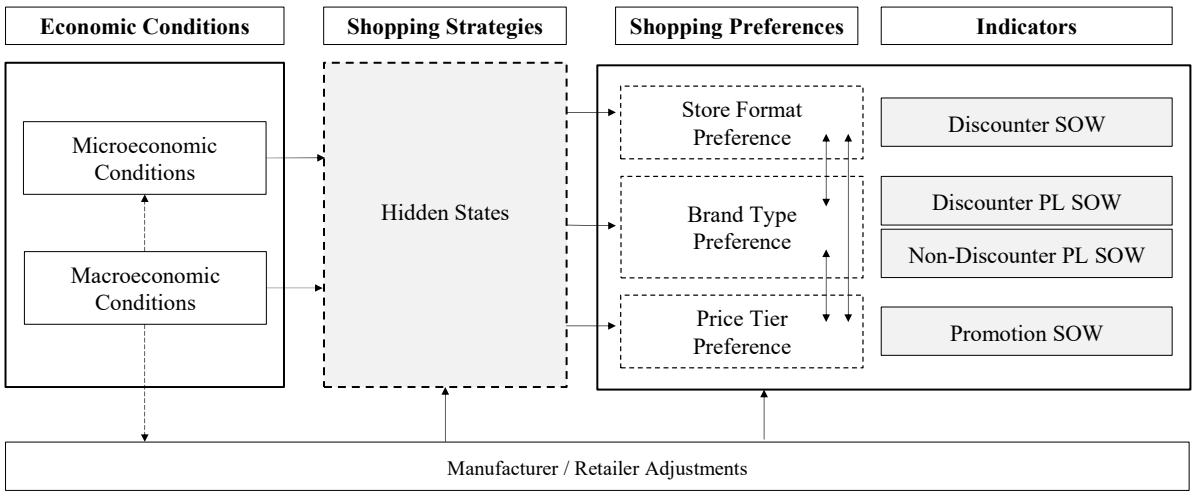
Dekimpe and Deleersnyder 2017; Ma et al. 2011) and advancing insights into differences across households, which previously have been addressed mainly by conceptual (Quelch and Jocz 2009) or survey-based (Hampson and McGoldrick 2013; Shama 1981) research. Our study derives insights from longitudinal, household-level field data while controlling for supply-side activities. Our results therefore offer high external validity.

Third, this study disentangles the effects of changes in microeconomic conditions, macroeconomic expansions, and macroeconomic contractions while also accounting for their different magnitudes. Studies to date mostly focus on macroeconomic conditions (Lamey 2014; Lamey et al. 2007) or use microeconomic conditions as time-invariant control variables (Cha et al. 2015; Ma et al. 2011). We instead observe household-specific changes in microeconomic conditions, such that we can analyze how households switch shopping strategies when their *ability* to purchase (Katona 1979) is directly affected due to changing conditions at a macroeconomic level. Dubé, Hitsch, and Rossi (2018) observe the effects of microeconomic conditions in terms of income and wealth over time. Their analysis focuses on PLs and controls for macroeconomic conditions using dummy variables for recession and post-recession periods; we instead explicitly analyze changes in macroeconomic conditions with different magnitudes. In addition, we differentiate macroeconomic expansions and contractions, which have asymmetric effects on households' shopping preferences (Dekimpe, Peers, and van Heerde 2016; Deleersnyder et al. 2004; Lamey et al. 2007). Furthermore, by controlling for microeconomic conditions in terms of households' ability to purchase, adjustments that follow shifting macroeconomic conditions constitute changes in households' *willingness* to purchase (Katona 1979). We further highlight the distinction between a household's ability and willingness to purchase in the following section.

3 Conceptual Framework

As depicted in our conceptual framework in Figure 1, micro- and macroeconomic conditions constitute our focal independent variables. Katona (1979) first established that changes in the overall economy affect individual households. For example, during a recession, wage levels drop and unemployment rises, which result in individual households suffering from income reductions. Thus, macroeconomic conditions influence households by directly affecting their microeconomic conditions and their ability to spend money. However, they also can affect households more indirectly, in terms of their willingness to purchase. A declining economy may diminish a household's confidence in its future microeconomic situation and make it less inclined to spend money; a growing economy may increase its confidence and make it more willing to spend (Katona 1979). Microeconomic conditions also change independent of macroeconomic conditions, but in either case, changing conditions lead households to adjust their shopping preferences.

Figure 1: Conceptual Framework



Notes: PL = private label; SOW = share of wallet.

Adjusting purchase quantities often is not a viable option for FMCGs, so changes to macro- and microeconomic conditions and in households' ability and willingness to purchase lead the households to seek to adjust the prices they pay. They can do so in three distinct ways, namely, by adjusting their store format preferences, brand type preferences, and price tier preferences. These preferences have substantial managerial relevance as manufacturers and retailers can address them in their marketing mix strategy, and as they directly influence their bottom lines. Due to their conceptual and managerial relevance, these three shopping preferences have been the focus of substantial prior literature (e.g., Cha et al. 2015; Dubé, Hitsch, and Rossi 2018; Lamey et al. 2007; Ma et al. 2011).

To measure store format preference, we use the household's discounter SOW, that is, the SOW that it devotes to discount store formats. For brand type preference, we use a household's SOW on (1) discounters' PLs, or discounter PL SOW, and (2) PLs in all other store formats, which we refer to as supermarket PL SOW.[1] By splitting brand type preference into two indicators, we gain a more detailed view. For example, households might prefer buying PLs in supermarkets due to their better perceived quality relative to PLs offered by discounters (Dhar and Hoch 1997). Alternatively, households might prefer to purchase NBs from discounters to take advantage of their everyday low price strategy. Finally, we measure price tier preference as a household's SOW spent on products on temporary price reduction, or price promotion SOW.

Strategic differences mark supermarkets, which usually adopt a high/low pricing strategy and carry primarily NBs, versus discounters, which take an everyday low price strategy and carry mostly PLs. Accordingly, purchase preferences and their indicators are highly interdependent (Dekimpe and Deleersnyder 2017; Dekimpe et al. 2011; Lamey 2014). Households shopping at discounters, for example, almost automatically end up purchasing more

[1] For simplicity, and because they account for the majority of other store formats, we refer to all non-discounter store formats as supermarkets hereafter.

PLs and fewer products on price promotion than those buying from supermarkets. Consequently, we model the multiple shopping preferences simultaneously in terms of their indicators and explicitly account for their interdependencies.

We also assume that a household's unique combination of shopping preferences is the result of its underlying shopping strategy. Different combinations of shopping preferences constitute different shopping strategies, which are not directly observable but can be captured as hidden states in our HMM formulation. Each hidden state reflects a particular, latent shopping strategy, composed of distinct combinations of shopping preferences and the underlying values observed for discounter SOW, discounter PL SOW, supermarket PL SOW, and price promotion SOW. Furthermore, unlike most previous HMM applications in marketing (e.g., Kumar et al. 2011; Netzer, Lattin, and Srinivasan 2008; Ngobo 2017), we allow households to switch among the hidden states without restriction, which is important conceptually, because there is no natural order to the shopping strategies that the hidden states reflect. For example, a household might save money by purchasing NBs in discounters or PLs in supermarkets. Both are distinct shopping strategies, without one naturally following or preceding the other. In order to derive a shopping strategy for each household in each period, we observe its shopping preference indicators. By observing households over time, we can assess how each household adjusts its shopping preferences by switching its shopping strategies in response to changes in macro- or microeconomic conditions. We thus detect heterogeneous adjustment patterns by households that originate from and switch into different shopping strategies.

So far, we have taken a household perspective. Yet prior research conclusively shows that retailers and manufacturers react to macroeconomic conditions too, such as by adapting their marketing mix (e.g., Deleersnyder et al. 2009; Lamey et al. 2012; Sudhir, Chintagunta, and Kadiyali 2005). We are less concerned with this relationship per se, yet we still need to control

for adjustments in the marketing mix due to their substantial influence on households' shopping behavior, in the short and long run. Therefore, we control for these effects by including marketing mix variables in the model estimating the hidden states to capture their long-term effects and in the model estimating the indicators to capture their short-term effects (e.g., Netzer, Lattin, and Srinivasan 2008).

4 Data and Identification

4.1 Research Context

The empirical setting is the German grocery retail market. It reached €183.5 billion in sales revenues and a growth rate of 3.5% in 2017, signaling the largest jump in its steady growth trend since the financial crisis (GfK 2017). Discounters are the dominant store format, accounting for 42.7% of the market's value, ahead of supermarkets, hypermarkets, and drugstores. The market also is highly concentrated, particularly in the supermarket format, where Edeka and Rewe account for over 90% of sales revenues (Kantar Consulting 2018). In their attempts to confront the market power of discounters and appeal to more shoppers, supermarkets have evolved to primary promoters of PLs in recent years; they now account for 37.4% of that market's value (GfK 2017).

To reflect the peculiarities of the German grocery retail market, our data set combines several sources and information across distinct aggregation levels. The primary data source is the ConsumerScan panel, provided by GfK Germany, which includes transaction and survey data for panelists at the individual household level. As a major advantage, the ConsumerScan panel covers private consumption comprehensively and representatively, including all German food retailers, specialty stores, drugstores, and discount stores that typically do not offer data for market research purposes through retail panels. This data availability is particularly crucial, considering the substantial market share of discount stores in Germany. The panel also contains

survey data for all panelists, based on self-reported annual information (age, household size, income). We obtain weekly data about brand-level advertising spending across multiple channels for all major manufacturers and retailers from the Nielsen Company, to control for advertising effects. Finally, publically available gross domestic product (GDP) data from the Federal Statistical Office indicate the aggregate economic situation. Overall, we thus build a unique, encompassing data set that combines behavioral measures with survey-based household demographics, aggregated economic measures, and brand-level advertising data.

4.2 Data Preparation

The initial raw data set from the ConsumerScan panel is composed of household characteristics and purchase decisions by 95,403 unique households that made more than 15 million shopping trips and 55 million purchases between 2006 and 2014. Purchase information is available at the stockkeeping unit (SKU) level for 39 product categories from 510 retailers, most of which maintain multiple stores. These products range from alcoholic and non-alcoholic beverages (e.g., beer, fruit juice) to food (e.g., cereals, pasta, ice cream) to non-food items (e.g., deodorants, detergents, toilet paper). For each purchased item, we have access to the unique product code, date and place of purchase, price paid, identifiers of the store format and brand type, and temporary price reductions, as well as specific product characteristics like the brand name, manufacturer name, and pack size. In preparing these data, we undertook several cleaning and filtering steps at the purchase record and household levels. In particular, we eliminated inconsistent transaction records and households that did not remain in the panel for the entire period. Thus, we obtain a panel data structure, rather than a repeated cross-sectional structure, as is commonly used in HMM applications in marketing. Because the sample composition does not differ by observation period, we can identify individual shopping strategies across households, as well as strategy adjustments based on within-household

variations over time. This procedure is conservative but in line with prior literature (e.g., Dubé, Hitsch, and Rossi 2018).

On the transaction record level, data cleaning involved the following steps:

1. Remove cases with missing product codes, brand type identifiers, category identifiers, or store format identifiers.
2. Remove all cases with unusually large (more than four times the median price) or unusually small (less than one-fourth the median price) prices at the SKU level.
3. Remove all cases with SKUs purchased fewer than 25 times in the entire period.
4. Remove all cases from three product categories (i.e., ketchup, body care, and lemon juice/lemon seasoning) due to inconsistent availability throughout the period.

With this data cleaning, we still preserve 97.4% of all observations and 96.0% of all expenditures.

On the household level, the filtering procedure involved the following selection criteria. To exploit the analytical potential of panelists with long purchase histories and extensive survey information, each panelist had to have:

1. At least one transaction per quarter from 2006 to 2014.
2. Available survey information on key demographics from 2006 to 2014.

In total, we identified and selected 5,421 unique households that met these requirements. We compared the filtered households with the remaining households according to key shopping preference indicators and demographic characteristics to avoid structural differences between samples. Overall, we find only marginal deviations in their purchase behavior and demographic composition. Therefore, we assume households with extensive purchase histories are not structurally different in their purchase behavior or demographic characteristics from households with shorter or incomplete purchase histories. We also compared our filtered sample with official information from the 2006 Microcensus (Destatis 2008). Our sample is slightly older,

with higher income, fewer single and more two-person households, and fewer children, yet we also still find sizable overlap in the distributions of the demographic variables. Similar demographic deviations between scanner data samples and census information also appear in previous literature (e.g., Dubé, Hitsch, and Rossi 2018). We control for these demographics on the individual household level throughout our empirical analysis. Hence, a lack of sample representativeness is not an issue. Detailed comparisons of the raw, filtered, and remaining household samples are available in Appendix A.

4.3 Variable Operationalization

Table 2 contains an overview of all variables included in the estimation process. Our model uses four indicator variables, representing shopping-related preferences, to uncover latent shopping strategies from observable purchase behavior: a household's discounter SOW, discounter PL SOW, supermarket PL SOW, and price promotion SOW. Each indicator variable corresponds to the ratio of the household's quarterly expenditures (in €) for the object of interest (i.e., products in discount store formats, PL products in discount and supermarket store formats, and products on temporary price promotion) to the household's total quarterly expenditures (Ailawadi, Pauwels, and Steenkamp 2008).

The modeling approach also includes explanatory variables to capture the influences of a household's individual micro- and the overall macroeconomic conditions. Microeconomic conditions reflect a household's individual financial situation, captured by the monthly net income of the household's principal earner, measured in 16 income brackets.[2] Macroeconomic conditions include the overall state of the business cycle, captured by economic expansion and economic contraction. That is, we apply the Christiano-Fitzgerald random-walk filter

[2] The income brackets are as follows: (1) <500 €, (2) 500-749€, (3) 750-999 €, (4) 1000-1249 €, (5) 1250-1499 €, (6) 1500-1749 €, (7) 1750-1999 €, (8) 2000-2249 €, (9) 2250-2499 €, (10) 2500-2749 €, (11) 2750-2999 €, (12) 3000-3249, (13) 3250-3499€, (14) 3500-3749, (15) 3750-3999, and (16) >4000€

(Christiano and Fitzgerald 2003) to log-transformed quarterly GDP data from Germany to extract the cyclical component of the series; it constitutes the cyclical deviation from the long-term trend in the log-transformed GDP series. Economic expansions (contractions) are periods with an increase (decrease) in the cyclical component. The magnitude of an expansion (contraction) at any point in time then can be defined as the difference between the level of the cyclical component at time t and the prior trough (peak) in the cyclical series (Lamey et al. 2007; Van Heerde et al. 2013).

Table 2: Variable Operationalization

Variable Group	Variable	Operationalization
Shopping Behavior Dimensions	*DiscSOW*	Expenditures (in Euros) in discounters divided by total expenditures per quarter.
	PLDiscSOW	Expenditures (in Euros) on PLs in discounters divided by total expenditures per quarter.
	PLSupSOW	Expenditures (in Euros) on PLs in supermarkets divided by total expenditures per quarter.
	PromoSOW	Expenditures (in Euros) on price promoted products divided by total expenditures per quarter.
Micro- and Macroeconomic Conditions	*Expansion*	Difference between the cyclical GDP component at time t and the prior trough.
	Contraction	Difference between the cyclical GDP component at time t and the prior peak.
	Income	Monthly net income of the household's principal income earner in 16 buckets (1 = lowest bucket, 16 = highest bucket)
Demographic Controls	*HHSize*	Number of persons in the household.
	Age	Age of the household leading person in 12 buckets. (1 = lowest bucket, 12 = highest bucket)
	Kids	Number of children in the household under the age of 14.
Marketing Mix Controls	*PriceDisc*	Weighted average price of discounters relative to weighted average price across store formats, with weights being households' store format SOWs.
	PricePLDisc	Weighted average price of PLs in discounters relative to weighted average price across brand types and store formats, with weights being households' brand type in store format SOWs.
	PricePLSup	Weighted average price of PLs in supermarkets relative to weighted average price across brand types and store formats, with weights being households' brand type in store format SOWs.
	AssrtDisc	Weighted number of unique SKUs in discounter relative to weighted number of unique SKUs across store formats, with weights being households' store format SOWs.
	AssrtPLDisc	Weighted number of unique SKUs of PLs at discounter relative to weighted number of unique SKUs across brand type and store formats, with weights being households' brand type in store format SOWs.
	AssrtPLSup	Weighted number of unique SKUs of PLs at supermarkets relative to weighted number of unique SKUs across brand type and store formats, with weights being households' brand type in store format SOWs.
	PricePromo	Weighted number of SKUs sold in price promotion relative to weighted number of SKUs sold across price tiers, with weights being household's price tier SOWs.
	AdvDisc	Weighted advertising spending (in Euro) cumulated over discounters relative to weighted advertising spending cumulated across store formats, with weights being households' store format SOWs.
	AdvPL	Weighted advertising spending (in Euro) cumulated over brands from brand type PL relative to weighted advertising spending cumulated across brands from all brand types, with weights being households' brand type SOWs.
Time Controls	*Time*	Continuous time variable
	Quarter	Indicator variable for quarters of the year

We include demographic characteristics as controls, such as the size of the household, age of the household head, and number of children in the household. Finally, we construct marketing mix controls based on households' purchase information and manufacturers' and retailers' advertising spending data similar to Ma et al. (2011). These control variables include weighted relative price indices, weighted relative assortment size indices, a weighted relative price format index, and weighted relative advertising indices. We use relative measures for the marketing mix variables to parsimoniously control for cross-effects of alternative store formats, brand types, and price tiers, respectively. The household-specific weights emphasize changes in the marketing mix that are relevant to a household given its usual shopping preferences. Appendix B offers details regarding the construction of the marketing mix variables. In addition, Table 3 provides descriptive statistics and correlations for all specified variables.

Table 3: Descriptives and Correlation Matrix

	Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	DiscSOW	41.03	28.55																		
2	PLDiscSOW	27.72	23.46	**.85**																	
3	PLSupSOW	7.75	9.91	**-.35**	**-.26**																
4	PromoSOW	25.81	21.95	**-.17**	**-.31**	**-.07**															
5	Expansion	2.06	.03	**.01**	-.01	**-.03**	**-.06**														
6	Contraction	1.14	.02	**.01**	**.01**	**-.01**	**-.03**	**-.39**													
7	Income	8.64	3.75	**-.11**	**-.07**	**-.05**	**.04**	**-.02**	**-.01**												
8	HHSize	2.32	1.12	**.05**	**.04**	.01	**.06**	**.03**	**.02**	**.38**											
9	Kids	.27	.65	**.07**	**.08**	**.03**	.00	**.03**	**.02**	**.13**	**.66**										
10	Age	8.61	2.49	**-.03**	**-.02**	**-.09**	**-.03**	**-.07**	**-.04**	**-.16**	**-.44**	**-.50**									
11	PriceDisc	.80	.09	**.62**	**.58**	**-.12**	**-.17**	**-.01**	**-.03**	**-.08**	**.03**	**.08**	**-.03**								
12	PricePLDisc	.69	.10	**.55**	**.61**	.00	**-.20**	**.02**	**-.01**	**-.09**	**.02**	**.08**	**-.02**	**.87**							
13	PricePLSup	.66	.09	**.53**	**.58**	**-.01**	**-.15**	**-.05**	.00	**-.09**	-.01	**.05**	**.02**	**.81**	**.94**						
14	AssrtDisc	.67	.13	**.62**	**.57**	**-.10**	**-.16**	**-.13**	**-.02**	**-.08**	**.06**	**.09**	**-.07**	**.91**	**.76**	**.70**					
15	AssrtPLDisc	.53	.19	**.53**	**.51**	**.02**	**-.18**	**-.13**	**-.02**	**-.08**	**.07**	**.11**	**-.11**	**.85**	**.76**	**.68**	**.94**				
16	AssrtPLSup	.33	.12	**.52**	**.50**	**.03**	**-.18**	**-.02**	**-.05**	**-.07**	**.07**	**.13**	**-.13**	**.84**	**.76**	**.70**	**.88**	**.96**			
17	PricePromo	.58	.09	**-.09**	**-.15**	.00	**.52**	**-.15**	**-.16**	**.03**	**-.08**	**-.07**	**.13**	**-.11**	**-.17**	**-.03**	**-.11**	**-.19**	**-.16**		
18	AdvDisc	1.10	.11	**-.29**	**-.26**	**.08**	**.06**	**-.11**	**.44**	**.03**	**-.02**	**-.02**	**.01**	**-.39**	**-.34**	**-.27**	**-.42**	**-.38**	**-.33**	**.09**	
19	AdvPL	.13	.18	**.11**	**.12**	**.05**	**.05**	**-.45**	**-.24**	**.03**	**-.05**	**-.04**	**.11**	**.20**	**.19**	**.22**	**.33**	**.33**	**.23**	**.28**	**-.41**

Notes: Bold figures indicate significance at $p < .001$. M = mean; SD = standard deviation.

5 Methodology

To achieve our objective to identify specific shopping strategies and uncover switching patterns among them, we specify an HMM to classify households into latent states of shopping behavior and allow for transitions across these latent states over time, which traditional latent class models cannot do. We assume that each latent state represents a specific shopping strategy, characterized by the household's observable discounter SOW, discounter PL SOW, supermarket PL SOW, and price promotion SOW. We assign each household to one latent state in the beginning of the time series, then note if they adjust their shopping behavior and transition into different latent states, driven by their individual micro- and general macroeconomic conditions.

In summary, the proposed HMM consists of three parts: (1) the initial model that estimates the probabilities of households being assigned to a certain latent state, (2) the transition model that estimates households' potential migration across latent states, and (3) a response model that specifies their observed shopping behavior. We detail each part next.

5.1 Initial State Model

According to the HMM logic, a starting condition must be specified, from which a certain household begins its trajectory through latent states over time. We define an initialization period at the beginning of our time series and use household sociodemographic information to estimate initial state memberships. Sociodemographic variables affect store format choices (Bell and Lattin 1998; Rhee and Bell 2002), PL shares (Ailawadi, Pauwels, and Steenkamp 2008), and promotional responses (Bell, Chiang, and Padmanabhan 1999). Therefore, we infer the likelihood of starting in a certain latent state from household sociodemographic characteristics, though we also consider these covariates in the initial state models to correct for observed household heterogeneity. As a further control for unobserved

household heterogeneity, we introduce a random effects factor, in the form of an individual-specific, normally distributed, unobserved variable F that captures time-invariant effects in households' initial state probabilities, as well as their transition probabilities across states over time. The probability of being in a given state initially can be estimated with a multinomial logit model. Formally, we define the probability of household h belonging to each of S latent states of shopping behavior at the beginning of the observation time t0 as:

$$(1) \qquad \Pr(S_{ht0}=s_{t0})=\frac{\exp\left(\alpha_{s_{t0}}+\lambda_{hs_{t0}}F_h+SocioDem_{ht0}\right)}{\sum_{s'}^{S}\exp(\alpha_{s_{t0}'}+\lambda_{hs_{t0}'}F_h+SocioDem_{ht0})},$$

where

$$(2) \qquad SocioDem_{ht0}=\beta_{s_{t0}}^{1,SocioDem}Income_{ht0}+\beta_{s_{t0}}^{2,SocioDem}HHSize_{ht0} +\beta_{s_{t0}}^{3,SocioDem}Age_{ht0}+\beta_{s_{t0}}^{4,SocioDem}Kids_{ht0},$$

such that $\alpha_{s_{t0}}$ is the fixed intercept for the initial state s_{t0}; $\lambda_{hs_{t0}}$ is the random intercept for individual household h in the initial state s_{t0}; F_h is a continuous latent factor that captures unobserved household heterogeneity; $SocioDem_{ht0}^{r}$ includes household-specific sociodemographic variables (r = 1, … , R) for the initialization period t0; and $\beta_{s_{t0}}^{r}$ captures the effects of the r-th variable on the probability of being in initial state s_{t0}.

5.2 Transition Model

From this assigned latent state, we assume households potentially adjust their shopping behavior in response to variations in their individual micro- and overall macroeconomic conditions. These shifts are captured in the model by allowing households to transition between latent states at each point in time. We do not impose any particular structure on the number of latent states or potential migrations among them; instead, the data determine existing shopping

strategies and how households transition across them. To account for other potential sources of adjusted shopping strategies, we control for supply-side effects with various marketing mix variables and household demographics. We again include the random effects factor F to control for unobserved household heterogeneity. Thus, our model can distinguish cross-household heterogeneity from time dynamics, such that the different households can have different levels of stickiness to latent states (Netzer, Ebbes, and Bijmolt 2017). We define the probability of household h moving from latent state s_{t-1} to state s_t as

(3) $$\Pr(S_{ht}=s_t \mid S_{ht-1}=s_{t-1},\ F_h, Econ_{ht}, Mix_{ht}, Dem_{ht}, Time_t) = \frac{\exp\left(\alpha_{s_{t-1},s_t}+\lambda_{hs_t}F_h+Econ_{ht}+Mix_{ht}+Dem_{ht}+\delta_{s_t}Time_t\right)}{\sum_{s'}^{S}\exp(\alpha_{s_{t-1},s_t'}+\lambda_{hs_t'}F_h+Econ_{ht}+Mix_{ht}+Dem_{ht}+\delta_{s_t'}Time_t)},$$

with

(4) $$Econ_{ht}=\beta^{1,Econ}_{s_{t-1},s_t}Income_{ht}+\beta^{2,Econ}_{s_{t-1},s_t}Expansion_{t-1}+\beta^{3,Econ}_{s_{t-1},s_t}Contraction_{t-1},$$

(5) $$Mix_{ht}=\beta^{1,Mix}_{s_{t-1},s_t}PriceDisc_{ht-1}+\beta^{2,Mix}_{s_{t-1},s_t}PricePLDisc_{ht-1}+\beta^{3,Mix}_{s_{t-1},s_t}PricePLSup_{ht-1} +\beta^{4,Mix}_{s_{t-1},s_t}AssrtDisc_{ht-1}+\beta^{5,Mix}_{s_{t-1},s_t}AssrtPLDisc_{ht-1}+\beta^{6,Mix}_{s_{t-1},s_t}AssrtPLSup_{ht-1} +\beta^{7,Mix}_{s_{t-1},s_t}PricePromo_{ht-1}+\beta^{8,Mix}_{s_{t-1},s_t}AdvDisc_{ht-1}+\beta^{9,Mix}_{s_{t-1},s_t}AdvPL_{ht-1}, \text{ and}$$

(6) $$Dem_{ht}=\beta^{1,Dem}_{s_{t-1},s_t}HHSize_{ht}+\beta^{2,Dem}_{s_{t-1},s_t}Age_{ht}+\beta^{3,Dem}_{s_{t-1},s_t}Kids_{ht},$$

where α_{s_{t-1},s_t} is the fixed intercept for the transition from latent state s_{t-1} to latent state s_t; λ_{hs} is the random intercept for individual household h in state s_t; F_h is a continuous latent factor that captures unobserved household heterogeneity; $Econ_{ht}$ includes variables representing (household-specific) economic conditions (p = 1, … , P), such that $\beta^{p,\,Econ}_{s_{t-1},s_t}$ captures the influence of the p-th variable on the transition from state s_{t-1} to s_t; Mix_{ht-1} includes household-specific marketing mix controls (m = 1, … , M), with $\beta^{m,\,Mix}_{s_{t-1},s_t}$ capturing the influence of the m-th marketing mix control on the transition from state s_{t-1} to s_t; Dem_{ht} includes controls on

household demographics (n = 1, … , N), with $\beta^{n,\,Dem}_{s_{t-1},s_t}$ capturing the influence of the n-th demographic control on the transition from state s_{t-1} to s_t; and $Time_t$ is a continuous time trend variable, such that δ_{s_t} captures its effect on the probability of being in state s_t.

5.3 Response Model

The final part of the HMM connects the latent states of shopping behavior to the observable outcomes of specific shopping preferences (i.e., discounter SOW, discounter PL SOW, supermarket PL SOW, and price promotion SOW) for a given household at a specific point in time. Thus, a household's observable preferences are an outcome of its membership in a specific state. Conditional on the latent state, the four preference indicator variables follow a multivariate normal distribution with no restrictions on the variance-covariance matrix, to account for potential interrelations between these outcomes.

We control for the possibility that households' observed shopping behavior is differently affected by short-term marketing actions, according to their current latent state membership. Concretely, we model the four dependent preference indicator variables as follows:

(7) $$DiscSOW_{ht}=\alpha^{Disc}_{s_t}+\beta^{1,Disc}_{s_t}PriceDisc_{ht}+\beta^{2,Disc}_{s_t}AssrtDisc_{ht}+\beta^{2,Disc}_{s_t}AdvDisc_{ht}+\gamma^{Disc}_{s_t}DiscSOW_{ht-1}+\delta^{Disc}Quarter_t+\varepsilon^{Disc}_t,$$

(8) $$PLDiscSOW_{ht}=\alpha^{PLDisc}_{s_t}+\beta^{1,PLDisc}_{s_t}PricePLDisc_{ht}+\beta^{2,PLDisc}_{s_t}AssrtPLDisc_{ht}+\beta^{2,PLDisc}_{s_t}AdvPL_{ht}+\gamma^{PLDisc}_{s_t}PLDiscSOW_{ht-1}+\delta^{PLDisc}Quarter_t+\varepsilon^{PLDisc}_t,$$

(9) $$PLSupSOW_{ht}=\alpha^{PLSup}_{s_t}+\beta^{1,PLSup}_{s_t}PricePLSup_{ht}+\beta^{2,PLSup}_{s_t}AssrtPLSup_{ht}+\beta^{2,PLSup}_{s_t}AdvPL_{ht}+\gamma^{PLSup}_{s_t}PLSupSOW_{ht-1}+\delta^{PLSup}Quarter_t+\varepsilon^{PLSup}_t, \text{ and}$$

(10) $$PromoSOW_{ht}= \alpha^{Promo}_{s_t}+\beta^{1,Promo}_{s_t}PricePromo_{ht}+\gamma^{Promo}_{s_t}PromoSOW_{ht-1}+\delta^{Promo}Quarter_t+\varepsilon^{Promo}_t,$$

where α_{s_t} is the intercept for the respective dependent variable, indicating that shopping behavior varies across latent states s_t. We also include the lagged dependent variables ($DiscSOW_{ht-1}$, $PLDiscSOW_{ht-1}$, $PLSupSOW_{ht-1}$, $PromoSOW_{ht-1}$), to capture households' inertial shopping behavior in each respective equation (γ_{s_t}). We allow those coefficients to vary across latent states s_t. Then the marketing mix variables ($PriceDisc_{ht}$, $PricePLDisc_{ht}$, $PricePLSup_{ht}$, $AssrtDisc_{ht}$, $AssrtPLDisc_{ht}$, $PricePromo_{ht}$, $AdvDisc_{ht}$, $AdvPL_{ht}$) aim to capture the respective state-specific supply-side effect β_{s_t}. Finally, we include $Quarter_t$ to capture potential seasonal effects δ in each equation and ε_t as an error term.

6 Results

6.1 Model Estimation and Selection

We use Latent GOLD 5.1 (Vermunt and Magidson 2016) to estimate the proposed HMM model with maximum likelihood; it can establish parameter estimates on the basis of a combination of expectation maximization and Newton Raphson iterations. The E-step computations use a generalization of the Baum-Welch algorithm (Baum et al. 1970) to circumvent excessive computational demands in applications with many time points (Ramos, Vermunt, and Dias 2011). To identify maximum likelihood parameter estimates, we consider 50 random sets of starting values and up to 5,000 expectation maximization iterations, followed by up to 50 Newton Raphson iterations per model estimation. All our models converged before reaching these maximum numbers of iterations. The large number of starting sets and expectation maximization iterations at the start considerably increases the probability of finding a global solution (Vermunt and Magidson 2016).

We use 2006 as the initialization period and data from 2007–2014 for the analysis. For computational feasibility, we rely on a random sample of 1,000 households from the filtered

data set for the final model estimations. Except for the time controls, we standardized all variables for the estimation process.

Because we have no prior knowledge about the exact number of latent states, nor do we impose restrictions on the state composition according to conceptual assumptions, we estimate a set of models with increasing numbers of states (1 to N), then select the model that offers the best fit to our data. Following prior research (e.g., Ngobo 2017), we rely on the consistent Akaike's information criterion (Bozdogan 1987) and Bayesian information criterion (Schwarz 1978); the former criterion offers a particularly strong probability of selecting the true model with large sample sizes, such as ours (Rust et al. 1995). Table 4 contains the information statistics we used for our model selection; they confirm that the seven-state model fits our data better than all other specifications.

Table 4: Model Fit Statistics

States	LL	BIC	CAIC	Parameters
1	-475,105.3	950,625.4	950,665.4	40
2	-469,176.3	939,369.2	939,467.2	98
3	-464,634.9	931,220.0	931,408.0	188
4	-460,647.3	924,510.4	924,820.4	310
5	-457,186.1	919,185.4	919,649.4	464
6	-455,245.8	917,234.4	917,884.4	650
7	**-453,711.4**	**916,426.9**	**917,294.9**	**868**
8	-452,434.0	916,465.6	917,583.6	1118

Notes: Numbers in bold indicate the best fitting solution. LL = log-likelihood; BIC = Bayesian information criterion; CAIC = consistent Akaike's information criterion.

6.2 Identified Shopping Strategies

In Table 5, Panel A, we summarize the identified latent states of shopping behavior, which indicate households' distinct shopping strategies. First, we note significant variation in the relative occurrence of each shopping strategy: Strategy 4 was adopted by households 52%

of the time, but Strategy 6 is present in only 1.1% of the cases. All other strategies show more equivalence, ranging from 6.4% of the observed time for Strategy 5 to 12% for Strategy 1. Second, some distinctive differences mark the strategies with regard to their underlying shopping preferences, as displayed in Figure 2. Compared with the sample averages (DiscSOW 40.3%, PLDiscSOW 27.7%, PLSupSOW 8.1%, PromoSOW 25.5%), households that pursue Strategy 4 show similar shopping preferences across all four indicators (DiscSOW 38.2%, PLDiscSOW 25.2%, PLSupSOW 7.6%, PromoSOW 25.2%). It is the most common shopping strategy, so we infer that it represents purchase behavior exhibited by the majority of households in various conditions. We refer to it as *Conventional Shopping.* All the other shopping strategies indicate particularly pronounced preferences in one way or the other. For example, among households that use Strategy 3, the preference indicators are all considerably below the population average; they prefer to shop at supermarkets at regular prices and particularly favor NBs (PLDiscSOW 15.8%, PLSupSOW 5.5%). Accordingly, we label this shopping strategy as *Brand Shopping.* Households that adopt Strategy 7 exhibit comparable preferences in store format and brand type, but they signal a particular interest in promotional offers (PromoSOW 51.5%), so that we label this strategy *Cherry Picking.* Households classified by Strategy 2 predominantly purchase in supermarkets but also indicate a strong focus on PL brands (DiscSOW 27.6%, PLSupSOW 21.0%), so we call this strategy *Supermarket Shopping.* With an intensification of this behavior, Strategy 6 pertains to households that exhibit the strongest preference for supermarket PL brands (PLSupSOW 39.9%), or the strategy we call *Supermarket PL Picking.* However, we again point out that this strategy occurs only 1.1% of the time, so it indicates a rather extreme strategy manifestation. Two other shopping strategies have a predominant focus on purchases from discount stores. Strategy 1 is characterized by the strongest preferences for the discount store format and PL brands across all identified strategies (DiscSOW 72.1%, PLDiscSOW 60.9%). We label it *Discounter Shopping.* Although

households pursuing Strategy 5 mainly purchase in discount store formats too, they aim to pick up NBs offered with temporary price reductions, rather than the discounters' PLs (PLDiscSOW 24.8%, PromoSOW 33.2%). Accordingly, we call this strategy *Discounter Brand Picking*; it is rather unconventional and may be driven by current retail developments, such that discounters are increasingly adding NBs to their assortments (Lourenco and Gijsbrechts 2013).

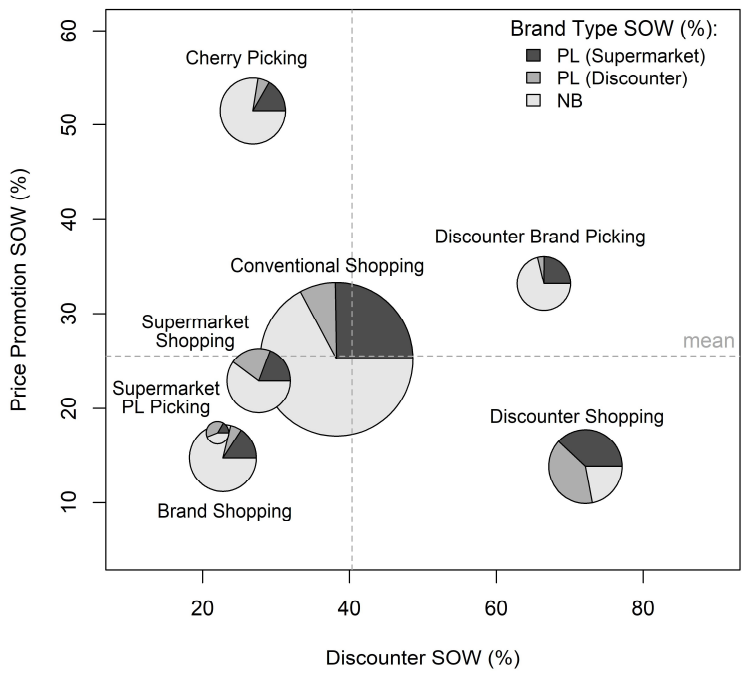
Table 5: Shopping Strategy Profiles

	Shopping Strategy							
Panel A	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Total**
Distribution (%)	12.0	8.9	10.0	52.0	6.4	1.1	9.5	100.0
Indicator (%)								
Discounter	72.1	27.6	22.8	38.2	66.5	22.0	26.8	40.3
PL (Discounter)	60.9	19.1	15.8	25.2	24.8	16.3	16.7	27.1
PL (Supermarket)	3.9	21.0	5.5	7.6	4.0	39.9	5.8	8.1
Price Promotion	13.8	22.9	14.7	25.2	33.2	17.4	51.5	25.5
Panel B								
Price Level	.903	1.012	1.228	1.1	1.014	.923	1.074	1.036
Volume (€)	122.2	125.5	111.9	175.0	125.8	78.9	150.0	127.0
Value (€)	115.5	131.4	139.4	199.3	132.7	77.2	165.6	137.3
Panel C								
Price Level dev. (%)	96.28	97.18	106.09	100.31	99.81	93.08	101.27	99.15
Volume dev. (%)	95.26	93.84	96.62	102.62	97.21	81.75	103.42	95.82
Value dev. (%)	91.94	91.63	101.89	102.78	97.22	77.19	104.79	95.35
Label	Discounter Shopping	Super-market Shopping	Brand Shopping	Conven-tional Shopping	Discounter Brand Picking	Super-market PL Picking	Cherry Picking	

Appendix C provides estimation results for the initial assignment of shopping strategies to households on the basis of their sociodemographic characteristics and their observable shopping behaviors. The initial shopping strategies are relevant; they indicate where households start their behavioral trajectory. For further insights into the nature of each individual shopping strategy, we use the posterior probabilities estimated in the HMM to assign each household to a specific strategy over time. For each strategy, we then calculate the average price households pay relative to the market price, the average volume purchased expressed in constant Euros,

and the average total spending when following a particular shopping strategy (Table 5, Panel B). This allows us to identify the spending levels associated with applying each of the strategies. With regard to the price level, households tend to spend the most with a Brand Shopping strategy (price level 1.228) and least with a Discounter Shopping strategy (price level .903). Households that adopt a Conventional Shopping strategy spend the most in absolute terms (value €199.3, volume €175.0), perhaps reflecting larger household sizes. The Supermarket PL Picking strategy (price level .923) is price focused to a similar degree as the Discounter Shopping strategy (price level .903). Furthermore, Discounter Brand Picking and Supermarket Shopping are similar in price levels (1.014 vs. 1.012), value spent (€132.7 vs. €131.4), and volume purchased (€125.8 vs. €125.5). This initial finding supports our intention to model holistic shopping strategies using multiple shopping preferences; households can maintain similar spending outcomes based on varying store formats, brand types, and price tier combinations. Finally, households employing the Cherry Picking strategy not only pay higher prices than the market average (price level 1.074) but purchase larger quantities too (volume €150.0), leading to rather high overall spending (value €165.6).

Figure 2: Shopping Strategy Comparison



6.3 Shopping Strategy Switching

Changing conditions affect households' ability or willingness to purchase, negatively or positively, so households may be motivated to switch their current shopping strategies in favor of strategies that better suit their present economic conditions. Such adjustments may depend directly on economic conditions, both up- and down-market. For market actors like NB manufacturers and retailers, knowledge about households' changing shopping strategies is critical for several reasons. First, they need insights about the general disposition or reluctance of specific household segments to change their shopping behavior in response to varying economic conditions. Then they can better predict the stability of their customer base, profits, or market shares. Second, information about switches from and to particular shopping strategies would provide insights into the complex transformations of customer bases. Identifying the previous shopping strategies of new customers and the subsequent strategies of defecting customers could enable firms to implement more effective marketing actions to attract and retain these shoppers. From a firm perspective, they need to know whether households adjust their shopping strategies, how, and in which direction.

In our empirical model, these adjustments are indicated by an increase or decrease of the transition probability between two particular shopping strategies, conditional on micro- and macroeconomic changes, as specified in Equation 3. Table 6 presents the transition matrix that depicts how households in general adjust their shopping strategies. The diagonal shows the probability that a household will maintain a specific shopping strategy. For example, 70.83% of the households retain a Conventional Shopping strategy from one period to another; this strategy thus appears rather persistent. Switching to Conventional Shopping also is a preferred transition for households following any other shopping strategy. The probabilities for maintaining any of the other shopping strategies instead are significantly lower, from 27.2% for Discounter Shopping to 2.69% for Supermarket PL Picking. Furthermore, except for the

transition to Conventional Shopping, we note substantial variation in the switching patterns across shopping strategies.

Table 6: Transition Matrix across Shopping Strategies

	Strategy (t – 1)						
	1	**2**	**3**	**4**	**5**	**6**	**7**
(in %)	Discounter Shopping	Supermarket Shopping	Brand Shopping	Conventional Shopping	Discounter Brand Picking	Supermarket PL Picking	Cherry Picking
Strategy (t)							
1	**27.20**	11.56	11.71	8.11	20.32	13.66	10.09
2	7.51	**10.38**	15.18	7.10	7.43	11.39	14.24
3	10.48	24.03	**9.72**	4.85	20.67	23.50	15.75
4	36.22	32.36	36.28	**70.83**	21.37	24.26	25.67
5	9.68	5.68	10.85	3.50	**7.98**	9.65	12.83
6	1.25	1.15	2.46	.43	2.43	**2.69**	2.46
7	7.66	14.82	13.80	5.17	19.80	14.85	**18.96**

Table 5 panel C presents the average deviation in the price households pay, the volume they purchase and their total spending when applying the respective strategy relative to when they use any of the other strategies. Hence, when households switch to Brand Shopping, they tend to pay higher prices (106.09%) but purchase less (96.62%). When households switch to Supermarket PL Picking, these deviations are most pronounced as households drastically reduce how much they pay, how much they purchase and, consequently, how much they spend in total. Given the results in the transition matrix, this makes sense, as households are most likely to switch into the Supermarket PL Picking strategy coming from the Brand Shopping and Cherry Picking strategies, which are both associated with high price and spending levels.

Table 7 indicates which significant effects lead households to adjust their shopping strategies. Among microeconomic conditions, low income increases households' probability to switch from Conventional Shopping to Discounter Shopping (-.198, $p < .01$), Discounter Brand Picking (-.303, $p < .01$), Supermarket Shopping (-.259, $p < .01$), or Supermarket PL Picking (-.391, $p < .1$), but it decreases the probability to switch to Brand Shopping (.175, $p < .1$).

Similarly, low income drives households to switch from Brand Shopping to Discounter Brand Picking (-.843, $p < .01$), Supermarket PL Picking (-1.363, $p < .01$), and Cherry Picking (-.667, $p < .1$), but it prevents them from switching from Discounter Shopping (.301, $p < .01$) to Brand Shopping. Finally, it induces households to change from Cherry Picking to Supermarket PL Picking (-.458, $p < .1$).

Table 7: Impact of Micro- and Macroeconomic Conditions on Strategy Transitions

Strategy in t – 1	Strategy in t	Variable	Coef.	SE	Z-value		Wald(0)		DF
		Income					135.342	***	42
1	**3**	**Income**	.301	.112	2.699	***			
3	**5**	**Income**	-.843	.339	-2.491	**			
3	**6**	**Income**	-1.363	.380	-3.584	***			
3	**7**	**Income**	-.667	.354	-1.886	*			
4	**1**	**Income**	-.198	.074	-2.667	***			
4	**2**	**Income**	-.259	.056	-4.626	***			
4	**3**	**Income**	.175	.106	1.650	*			
4	**5**	**Income**	-.303	.080	-3.793	***			
4	**6**	**Income**	-.391	.216	-1.805	*			
7	**6**	**Income**	-.458	.237	-1.931	*			
		Expansion					80.146	***	42
1	**5**	**Expansion**	.253	.137	1.851	*			
1	**7**	**Expansion**	.331	.181	1.827	*			
2	**1**	**Expansion**	-.366	.171	-2.148	**			
2	**5**	**Expansion**	-.334	.194	-1.723	*			
2	**6**	**Expansion**	-.807	.373	-2.163	**			
3	**1**	**Expansion**	-.679	.259	-2.619	***			
3	**4**	**Expansion**	-.489	.262	-1.868	*			
3	**7**	**Expansion**	-.723	.271	-2.671	***			
		Contraction					49.106		42
1	**5**	**Contraction**	.223	.119	1.877	*			
4	**7**	**Contraction**	.223	.109	2.052	**			
5	**7**	**Contraction**	.357	.187	1.908	*			

Notes: ***$p < .01$; **$p < .05$; *$p < .1$.
1 = Discounter Shopping; 2 = Supermarket Shopping; 3 = Brand Shopping; 4 = Conventional Shopping; 5 = Discounter Brand Picking; 6 = Supermarket PL Picking; 7 = Cherry Picking

These switches have severe and distinct consequences for firms, and Table 8 translates the positive and negative transition effects into clear consequences for NB manufacturers,

supermarkets, and discounters. It shows that low income induces particularly unfavorable consequences for NB manufacturers, because households either switch to a shopping strategy with less brand focus or avoid switching to a shopping strategy with a stronger brand focus. For supermarkets and discounters, the consequences are more ambivalent; households' transition from Conventional Shopping to Discounter Shopping is positive for discounters and negative for supermarkets, but some households with a Conventional Shopping strategy transition to Supermarket Shopping, implying reverse consequences for these market players.

Table 8: Strategy Transitions Due to Income Loss and Market Consequences

			Consequences for:		
Switches from	**Focal Strategy**	**Switches to**	**National Brands**	**Super-markets**	**Discounters**
Conventional Shopping ↗	**Discounter Shopping**	↘ Brand Shopping	–	–	+
Conventional Shopping ↗ Brand Shopping ↗	**Discounter Brand Picking**		–	–	+
Conventional Shopping ↗	**Supermarket Shopping**		–	+	–
Conventional Shopping ↗ Brand Shopping ↗ Cherry Picking ↗	**Supermarket PL Picking**		–	+	–
	Conventional Shopping	↗ Discounter Shopping ↗ Supermarket Shopping ↗ Discounter Brand Picking ↗ Supermarket PL Picking ↘ Brand Shopping	–	+ / –	+ / –
Discounter Shopping ↘ Conventional Shopping ↘	**Brand Shopping**	↗ Discounter Brand Picking ↗ Supermarket PL Picking ↗ Cherry Picking	–	+ / –	+ / –
Brand Shopping ↗	**Cherry Picking**	↗ Supermarket PL Picking	–	o	o
	Total Effect		**–**	**+ / –**	**+**

Notes: ↗ = increased probability to switch; ↘ = decreased probability to switch.

Economic expansions also have distinct effects on households' switching behaviors (Table 7). They encourage transitions from Discounter Shopping to Discounter Brand Picking (.253, $p < .1$) and Cherry Picking (.331, $p < .1$). Yet households' probabilities of switching from Supermarket Shopping to Discounter Shopping (-.366, $p < .05$), Discounter Brand Picking (-.334, $p < .1$), or Supermarket PL Picking (-.807, $p < .05$) decrease. Households appear reluctant to switch from Brand Shopping to Discounter Shopping (-.679, $p < .01$), Conventional Shopping (-.489, $p < .1$), or Cherry Picking (-.723, $p < .1$). In this sense, economic expansions imply primarily positive consequences for NB manufacturers and supermarkets but negative consequences for discounters as seen in Table 9.

Table 9: Strategy Transition Due to Economic Expansion and Market Consequences

				Consequences for:		
Switches from		**Focal Strategy**	**Switches to**	**National Brands**	**Super-markets**	**Discounters**
Supermarket Shopping Brand Shopping	↘ ↘	**Discounter Shopping**	↗ Discounter Brand Picking ↗ Cherry Picking	+	+	–
Supermarket Shopping Discounter Shopping	↘ ↗	**Discounter Brand Picking**		+	–	–
		Supermarket Shopping	↘ Discounter Shopping ↘ Discounter Brand Picking ↘ Supermarket PL Picking	+	+	–
Supermarket Shopping	↘	**Supermarket PL Picking**		+	+ / –	o
Brand Shopping	↘	**Conventional Shopping**		+	+	–
		Brand Shopping	↘ Discounter Shopping ↘ Conventional Shopping ↘ Cherry Picking	+	+	–
Discounter Shopping Brand Shopping	↗ ↘	**Cherry Picking**		+	+	–
		Total Effect		+	+ / –	–

Notes: ↗ = increased probability to switch; ↘ = decreased probability to switch

Households tend to shift their focus from discounter PLs toward NBs, sold by either discount stores (Discounter Brand Picking) or supermarkets on promotion (Cherry Picking). Therefore, switching strategies during economic expansions predominantly indicate upmarket shifts, in both brand type and store format. This situation intensifies for discounters, because households are reluctant to switch from brand- or supermarket-oriented strategies; they simply do not move downmarket toward discounters or PLs during prosperous economic times. Therefore, discounters are negatively affected by the defecting customer base and lack of customer gains from households switching strategies.

Finally, economic contractions drive switching too (Table 7). Mainly, households switch toward Cherry Picking by abandoning Discounter Brand Picking (.357, $p < .1$) and Conventional Shopping (.223, $p < .05$). We also find an increased likelihood that households switch from Discounter Shopping to Discounter Brand Picking (.223, $p < .1$). These strategy switches during economic contractions have negative consequences for discounters, positive ones for supermarkets, and mixed outcomes for NB manufacturers as seen in Table 10. The latter two actors primarily benefit from households' increasing focus on promotional items as they switch to Cherry Picking and Discounter Brand Picking strategies. The main downside for NB manufacturers is the risk of reduced margins, due to temporary price reductions. The switches are more generally unfavorable for discounters though, because households either stop visiting their stores or avoid purchasing more profitable PLs within these stores.

Table 10: Strategy Transitions Due to Economic Contraction and Market Consequences

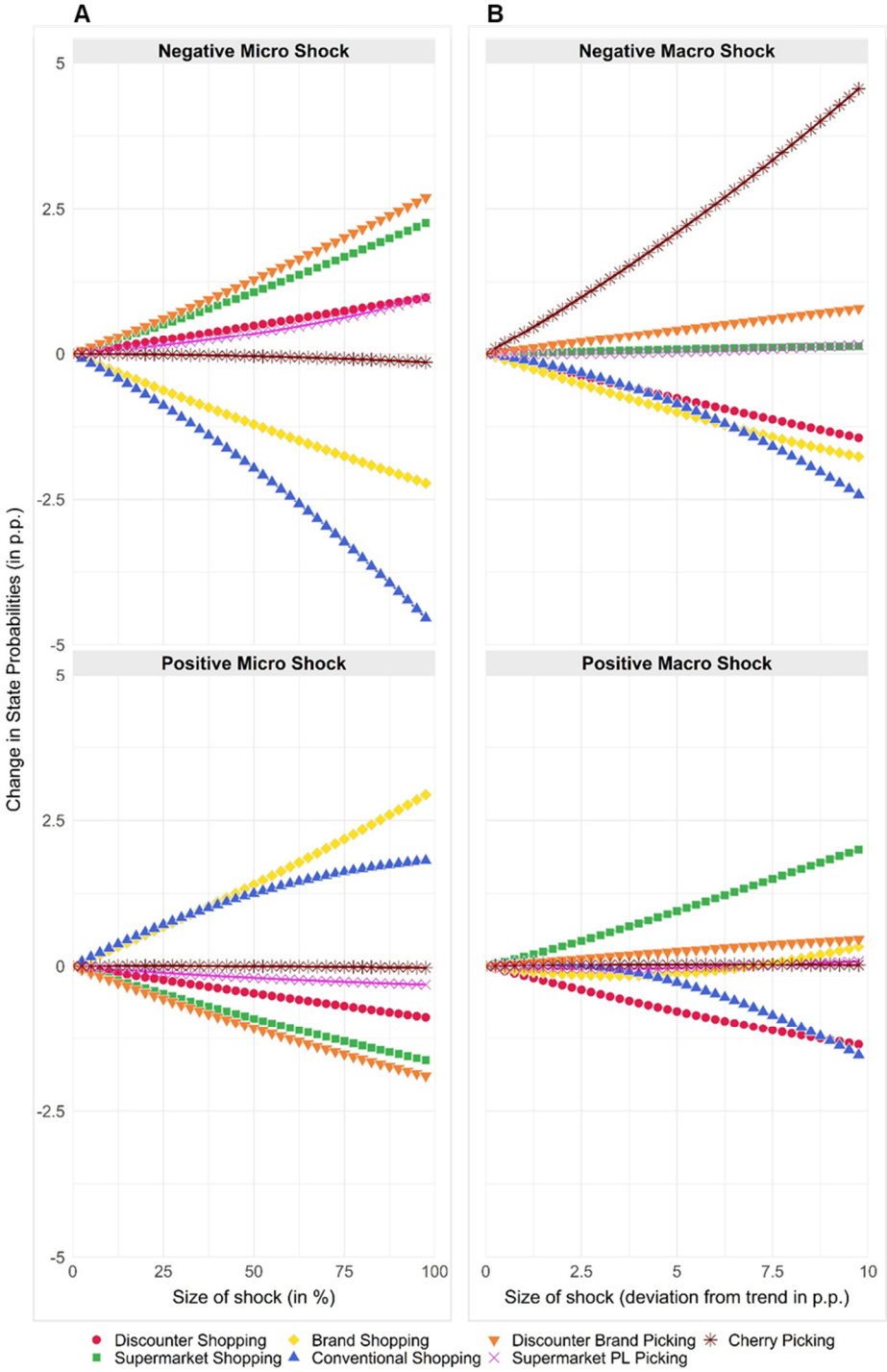
Switches from	Focal Strategy	Switches to	Consequences for: National Brands	Super-markets	Discounters
	Discounter Shopping	↗ Discounter Brand Picking	+	o	o
Discounter Shopping ↗	**Discounter Brand Picking**	↗ Cherry Picking	+	+	–
	Conventional Shopping	↗ Cherry Picking	+	+	–
	Brand Shopping	↗ Cherry Picking[a]	–	o	o
Discounter Brand Picking ↗ Conventional Shopping ↗ Brand Shopping[a] ↗	**Cherry Picking**		+	+	–
	Total Effect		+ / –	+	–

Notes: ↗ = increased probability to switch; ↘ = decreased probability to switch.
[a]based on transition matrix.

6.4 Sensitivity of Shopping Strategies

The results of our seven-state HMM specification provide valuable insights into the existence of distinct shopping strategies and switching behaviors across strategies, in response to varied micro- and macroeconomic conditions. To gain an even clearer picture of the sensitivity of each shopping strategy to gradually changing micro- and macroeconomic conditions, as often occur in reality, we next perform a series of simulations using the estimates from the preferred HMM solution. We thus construct four scenarios to reflect a positive microeconomic shock, negative microeconomic shock, positive macroeconomic shock, and negative macroeconomic shock. For each scenario, we run 40 simulations and induce shocks of increasing magnitude by gradually manipulating the sample average of the particular variable of interest. Thus, for a positive (negative) microeconomic shock, we gradually increase (decrease) mean income in 2.5pp increments; for a positive (negative) macroeconomic shock, we gradually increase the mean economic expansion (contraction) in .25pp increments. Figure 3 provides an overview of the simulation results.

Figure 3: Shopping Strategy Sensitivities to Economic Shocks



For microeconomic shocks, the probability changes for any of the shopping strategies are more pronounced for negative shocks, i.e., income losses than for positive shocks, i.e., income gains (Figure 3, Panel A). For example, a simulated income loss of -50% reduces the

probability of pursuing a Conventional Shopping strategy by -1.97pp, while an equivalent income gain increases the probability of this strategy only by +1.25pp. Thus, households' general willingness to adjust shopping behavior seems greater when they experience monetary losses rather than monetary gains. Otherwise, the shopping strategies' trajectories are largely intuitive and inversely symmetrical with regard to positive and negative shocks. Hence, these results support the external validity of our model.

Furthermore, income losses increase the probabilities of Discounter Shopping, Discounter Brand Picking, Supermarket Shopping, and Supermarket PL Picking strategies, but income gains decrease the probabilities of these strategies. These trajectories make sense, in that all these shopping strategies exhibit rather low price level indices (Table 5). The reverse is true for Conventional Shopping and Brand Shopping strategies: Their probabilities decrease with income losses, whereas they increase with income gains. These trajectories also align with the rather high price level indices of both strategies. In either case though, the probabilities of a Cherry Picking strategy do not tend to be affected by microeconomic shocks.

The picture differs when it comes to macroeconomic shocks. The probability changes for any shopping strategies seem more pronounced during negative shock, i.e., economic contractions than during positive shock, i.e., economic expansions (Figure 3, Panel B), yet the trajectories of some strategies evolve unsymmetrically and counterintuitively, across positive and negative shocks. The probability that households pursue the most price sensitive Discounter Shopping strategy decreases during both economic expansions and, contrary to intuition, contractions, with a similar magnitude. That is, an economic expansion of 5pp decreases the probability of a Discounter Shopping strategy by -.78pp, and an equivalent economic contraction decreases it by -.76pp. A similar pattern, with varying magnitudes across economic expansions and contractions, occurs for the less price sensitive Conventional Shopping strategy, such that a 5pp economic contraction (expansion) decreases the probability of this strategy by

-.86pp (-.28pp). Shocks in economic contraction and expansion also both increase the probability that households adopt a Discounter Brand Picking strategy, by +.42pp and +.25pp, respectively. Then other shopping strategies are sensitive only to either economic expansions or contractions. For example, a 5pp economic contraction shock increases the probability of pursuing a Cherry Picking strategy by +2.10pp, but an economic expansion has no effect. The Supermarket Shopping strategy instead is sensitive to economic expansions (+.94pp) but not to economic contractions.

Changes in households' income directly affect their ability to purchase. Because our simulations of macroeconomic shocks hold households' income constant, we isolate the more subliminal effects on households' willingness to purchase. In the case of contracting macroeconomic conditions, our results reveal these effects to be not directly apparent. We present possible explanations for these findings in the following section.

7 Discussion and Summary

We discuss our findings according to the research objectives stated at the outset of this article and contribute to existing literature by interpreting the reasons for the various shifts our results have uncovered. In addition, we specify some important, differential implications for each key player in the FMCG sector - manufacturers, supermarkets, and discounters - to offer concrete managerial actionability.

7.1 Identified Shopping Strategies

Our results reveal seven shopping strategies with distinct characteristics in terms of store, brand type, and price tier preferences. Conventional Shopping dominates, accounting for 52% of all observations and featuring balanced discounter SOW, PL SOW, and price promotion SOW, but distinct and diverse strategies make up the other half. Two strategies are

characterized by a large proportion of spending with discounters and differ primarily in terms of their discounter PL SOW (Discounter Shopping and Discounter Brand Picking). The other four shopping strategies all feature similar discounter SOW but differ in their supermarket PL SOW (Supermarket PL Shopping, Supermarket Shopping, and Brand Shopping) or price promotion SOW (Cherry Picking).

This variety highlights the heterogeneity in how households shop, as well as the importance of analyzing multiple shopping preferences to gain a holistic sense of households' shopping strategies. Four shopping strategies are similar in their store format preferences but diverge in their brand type and price tier preferences. These differentiations would remain hidden with a singular, aggregated perspective on shopping preferences (Dubé, Hitsch, and Rossi 2018; Lamey 2014; Lamey et al. 2007). Furthermore, these differences extend to the prices that households pay, the volume purchased, and the total spending associated with a certain strategy (Table 5, Panels B and C). Households spend most when they adopt a Cherry Picking strategy (104.79%). As some evidence has shown (Heilman, Nakamoto, and Rao 2002), price promotions seem to seduce households into paying higher prices (101.27%) and purchase larger quantities (103.42%) than usual. In contrast, households spend less when they pursue a Supermarket Shopping or Supermarket PL Shopping strategy than with the Discounter Brand Picking strategy, despite their substantially lower discounter SOW. These results align with current trends, in which discounters keep adding more NBs to their assortment (Lourenco and Gijsbrechts 2013) while supermarkets extend their PL assortments (Ailawadi, Pauwels, and Steenkamp 2008). We find further indicators for this development in the very existence of the Discounter Brand Picking and Supermarket PL Picking strategies. In the former case, households devote most of their SOW to NBs (71.2%) and pay above–market level prices (1.014). In the latter strategy, they instead devote 40% of their SOW to supermarket PLs and pay below–market level prices on average (.923).

7.2 Shopping Strategy Switching

The results from the transition model reveal that micro- and macroeconomic conditions indeed influence households' shopping strategies and, in turn, their shopping preferences. In addition, the estimated transition coefficients reveal *how* households react and uncover significant variation across households in their responses to changing conditions. These findings, based on a detailed modeling approach and longitudinal field data, have important diagnostic and normative value.

Notably, households adjust differently depending on the shopping strategy they use initially. When they suffer reduced income, for example, households previously engaged in Brand Shopping switch to a Cherry Picking strategy, increase their price tier preference, and accordingly purchase more products on promotion. Households already engaged in a Cherry Picking strategy cannot increase their purchases of products on promotion further, so instead, they turn to the Supermarket PL Picking strategy to cope with diminished income. Yet households originating from the same shopping strategy also might adjust to changing conditions by switching to different shopping strategies. For example, an income loss leads some households to adjust their price tier preference and switch from Brand Shopping to Cherry Picking, but others adjust their brand type preference and move to Supermarket PL Picking, while still others adjust their store format preference to adopt a Discounter Brand Picking strategy.

In terms of changes in *microeconomic conditions*, we find that all transitions caused by a loss in income entail movements from more expensive strategies, in terms of the price level and total wallet, to less expensive strategies. No clear tendency emerges in terms of whether households stick to a specific store format or brand type though. Instead, the various adjustment patterns across households boil down to four fundamental mechanisms that households apply to adjust to income losses: stick to the brand type but switch to a different store format (switch

to Discounter Brand Picking), stick with the store format but switch the brand type (switch to Supermarket Shopping or Supermarket PL Picking), stick with the store format and brand type but switch to seeking promotions (switch to Cherry Picking), or switch both, brand type and store format (switch to Discounter Shopping).

During *contracting macroeconomic conditions*, intriguingly, households switch to shopping strategies that are moderately more expensive. We present three possible explanations for this finding. First, a household that does not suffer an income loss during a countrywide contraction might feel more confident, relative to peers, so it experiences increased confidence and willingness to spend, or even a feeling of "invincibility." Hampson and McGoldrick (2013) similarly identify a class of households unaffected by financial crises that become even more careless in their spending. In terms of PL purchases, several studies caution that contractions do not necessarily increase PL consumption when controlling for household income (Dubé, Hitsch, and Rossi 2018; Kaswengi and Diallo 2015). Second, in stressful macroeconomic environments, households may compensate by making purchases of more expensive products, as predicted by coping literature (e.g., Burroughs and Rindfleisch 1997; Duhachek 2005; O'Guinn and Faber 1998). This effect could arise in response to income losses too, but in that case, households' more restrictive budgets may deter them from such compensatory shopping behavior. Similarly, the concept of frugal fatigue suggests that households grow tired of self-restricting behavior during contractions and therefore pursue compensatory purchases (Braak, Geyskens, and Dekimpe 2014; Dekimpe and Deleersnyder 2017). Both these explanations align with our finding that households switch to shopping strategies that are marginally more expensive. For example, during contractions, households switch from Discounter Shopping to Discounter Brand Picking; they still seem to be reluctant to consider the expensive Brand Shopping strategy. Households thus opt for "compromise strategies" such as Discounter Brand Picking or Cherry Picking. Third, given the tense overall environment that occurs during

contractions, households may become more deal prone and, therefore, switch to the Discounter Brand Picking and Cherry Picking strategies, which feature the largest price promotion SOWs. As a result, they unintentionally may end up engaged in shopping strategies that are more expensive and lead them to overspend. This is even true for the switches from Brand Shopping to Cherry Picking that we observe. Although households tend to pay higher prices in the Brand Shopping strategy, they purchase larger volumes in the Cherry Picking strategy and eventually spend more in total.

During *expansive macroeconomic conditions*, households instead embrace the positive climate and adopt shopping strategies associated with moderately higher spending; while the probability of transitions into strategies that are less expensive decreases. We again note the wide variety of adjustments across households. Yet in contrast with the effect of changes in microeconomic conditions, the strategies that households switch into when macroeconomic conditions improve are only marginally more expensive, and those into which they are less likely to switch are only marginally less expensive. Thus, a positive economic climate indeed encourages households to increase their spending levels, but they are notably more reserved than they appear to be in response to microeconomic income increases.

7.3 Sensitivity of Shopping Strategies

Our simulation results reveal the sensitivity of shopping strategies to changes in micro- and macroeconomic conditions of differing magnitudes. In aggregate, changes in microeconomic conditions and the associated deteriorating ability to purchase lead to more pronounced switches than changes in macroeconomic conditions affecting households' willingness to purchase. Furthermore, households react more strongly to deteriorating microeconomic conditions than to improving ones, in line with previous studies of durables (Deleersnyder et al. 2004) and PLs (Lamey et al. 2007).

Brand Shopping and Conventional Shopping strategies are both positively associated with microeconomic conditions. Whereas Brand Shopping acts as a ceiling strategy that even Conventional Shopping households eventually resort to given substantial income gains, no equivalent floor strategy appears in the case of income losses. We might predict the Discounter Shopping strategy would take this floor role, because it is the cheapest strategy, but instead, households seem reluctant to adopt it even after extreme income losses. Apparently, many households rather save elsewhere or use their savings than shop exclusively in discounters and purchasing their PLs.

In macroeconomic expansions, the positive overall climate leads households to abandon the Discounter Shopping strategy. Instead, the Supermarket Shopping strategy in particular becomes more likely. As the transition coefficients reveal, households become less likely to switch to cheaper shopping strategies. With particularly strong expansions, Conventional Shopping grows less likely to be adopted; households instead tend to stay with a Brand Shopping strategy. Given that we control for households' income, we can conclude that households are affected by the overall positive climate created by an expansion. Weak expansions make households more likely to switch to moderately more expensive shopping strategies and less likely to switch to moderately less expensive strategies; strong expansions and their positive effects on households' confidence lead to increasing adoptions of Brand Shopping, the most expensive shopping strategy.

Finally, during macroeconomic contractions, we observe an increase in Cherry Picking and Discounter Brand Picking, which feature the largest price promotion SOWs. Their growth is consistent according to the different magnitudes of macroeconomic contractions. This result points to the increased deal proneness of households during adverse macroeconomic conditions, as a consequence of the tense overall environment.

7.4 Managerial Implications

Our results reveal the existence of various shopping strategies and highlight how households switch strategies as a result of changing micro- and macroeconomic conditions. Although manufacturers and retailers have little control over these events, knowing the associated reactions by households allows them to optimize their marketing mix. In addition, managers might tailor their strategies to geographical regions, depending on how strongly affected each region is. Dubé, Hitsch, and Rossi (2018) show for example that unemployment rates after the Great Recession varied considerably among U.S. regions.

Implications for national brand manufacturers. Even as NBs lose market share as a whole when households experience income reductions, purchases of NBs from discounters and on price promotion increase. Thus, we propose two possible NB strategies when households suffer income reductions. First, manufacturers could increase their price promotion activities, catering to households that switch from Brand Shopping to Cherry Picking. This switch even tends to increase households' spending; they purchase greater volumes and end up spending more in total with this strategy. Second, managers could increase listings in discount store formats to cater to households that switch to a Discounter Brand Picking strategy.

Because households partly decrease their discounter SOW if they instead switch to Supermarket Shopping or Supermarket PL Picking strategies, NB managers also might increase their in-store promotional activities in these scenarios. Households transitioning away from Brand Shopping and Cherry Picking strategies may be accustomed to purchasing NBs. Changing shopping strategies to save money also depletes shoppers' cognitive resources and self-control (Stilley, Inman, and Wakefield 2010; Vohs and Faber 2007), which might be particularly challenging for households switching from a Brand Shopping strategy that does not involve any cost saving tactics. Shopping with a goal to save money may deplete these

households' cognitive resources more, leaving them more susceptible to in-store promotions (Gijsbrechts, Campo, and Vroegrijk 2018).

When conditions improve for households, whether on a micro- or macroeconomic level, they tend to adopt strategies with higher NB SOW. Therefore, NB managers should reallocate their budgets, according to favorable versus adverse conditions. Countercyclical marketing investments also have been suggested in prior literature (e.g., Lamey et al. 2007, 2012).

Implications for supermarkets. Supermarkets may lose market share to discounters, but they also enjoy an increase in PL purchases when households experience income reductions. Strengthening their PLs would give supermarket managers leverage over NB managers when negotiating prices, promotional activities, and advertising allowances. These managers also might want to increase their advertising spending during adverse conditions, with the dual purpose of strengthening their store image and their PLs. Line extensions to their PLs also could help supermarkets cater to the households considering a switch to Supermarket Shopping or Supermarket PL Picking, which households switch to when they move away from the Conventional Shopping strategies. Although these two strategies entail low discounter SOW, they also provide the lowest spending levels; they combine a low price premium paid and low volume purchased. In these situations, supermarkets might increase and encourage in-store promotions to boost spending levels or adopt traditional discounter strategies, such as offering larger package sizes.

Considering that both supermarkets and NBs lose customers to discounters when households' microeconomic conditions worsen, they might collaborate more closely, for example in terms of advertising allowances, feature promotions, price reductions, and price promotions with the goal to win back customers for both parties. Lourenco, Gijsbrechts, and Paap (2015) refer to "Lighthouse" product categories, whose pricing signals the store's price image to consumers, even though they account for only a small part of households' spending.

By strategically reducing prices in these product categories, managers can communicate a lower price image and potentially reduce transitions to strategies with larger discounter SOW, such as from Conventional Shopping to Discounter Shopping or Discounter Brand Picking.

Implications for discounters. Discounters stand to gain from adverse microeconomic conditions, because households switch to the Discounter Brand Picking and Discounter Shopping strategies. Working with NBs, discounters can extend their NB portfolio to increase switches to the Discounter Brand Picking strategy. This implication is in line with findings in prior literature (Deleersnyder et al. 2007; Deleersnyder 2012). The Discounter Brand Picking strategy also features the second largest price promotion SOW, so NBs and discounters might work together to offer more price promotions. However, discounters also should allocate some spending to periods associated with economic expansions, to keep households from switching back to supermarkets.

7.5 Limitations and Directions for Research

We seek to uncover heterogeneity in shopping strategies due to different combinations of store format, brand type, and price tier preferences. In doing so, we have focused on the most managerially relevant shopping preferences in FMCG settings but neglected other dimensions of FMCG shopping behavior that might be worth studying, such as the number of shopping trips, preferences for price tiers, or preferences for vice and virtue goods. Insights along these lines could help reveal the degree to which different types of households engage in approach or avoidance strategies during stressful periods (Duhachek and Oakley 2007).

In our model specification, we use SOWs to estimate parsimoniously how households allocate their budgets across different store formats, brand types, and price tiers. The post-hoc descriptive statistics give some indication of whether households actually realize savings when switching shopping strategies. Notably, switches to the Cherry Picking strategy carry the

potential to increase spending levels instead of reducing them. However, our model does not explicitly consider if and to what extent households change their spending levels when micro- or macroeconomic conditions change. Further research could deepen these insights by using absolute expenditures as dependent variables and uncovering household heterogeneity in realized savings.

Counterintuitively, we find that households engage in moderately more expensive shopping strategies during contractions, when we keep income constant. We offer some possible explanations; continued research should test these suppositions. For example, how do consumers behave during adverse macroeconomic conditions that do not affect them directly? Are they exposed to environmental stress, such that they suffer lower confidence; does a feeling of invincibility set in; or do they capitalize on their relatively better standing by engaging in more conspicuous consumption?

Furthermore, we take a disaggregate view on households but aggregate product categories. Studying how households adjust their shopping behavior across different product categories, such as for utilitarian versus hedonic goods, may provide further insights and grant product managers more relevant information. Researchers might seek to identify product categories that are particularly susceptible or resistant to changes in consumers' shopping strategies.

References Paper II

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Appendix Paper II

Appendix A: Data Preparation

Table A1: Comparison of Raw and Cleaned ConsumerScan Sample

Year	Sample	Households	Trips	Observations	Expenditures (€)
2006	Raw	27,238	1,516,399	5,308,146	12,277,215
	Cleaned	27,221	1,495,333	5,121,013	11,694,059
2007	Raw	25,293	1,526,362	5,261,490	12,494,743
	Cleaned	25,284	1,508,387	5,106,354	11,996,645
2008	Raw	24,651	1,512,122	5,185,341	12,877,456
	Cleaned	24,639	1,494,801	5,038,442	12,400,021
2009	Raw	24,646	1,474,450	5,051,000	12,556,951
	Cleaned	24,632	1,457,770	4,909,630	12,096,259
2010	Raw	33,572	1,928,991	6,928,282	16,774,079
	Cleaned	33,554	1,913,414	6,768,848	16,111,015
2011	Raw	34,563	1,909,825	6,876,423	17,013,584
	Cleaned	34,552	1,894,666	6,721,440	16,365,427
2012	Raw	37,738	1,932,679	6,893,542	17,413,688
	Cleaned	37,728	1,917,517	6,737,337	16,755,645
2013	Raw	36,559	1,951,850	6,979,813	17,490,674
	Cleaned	36,545	1,936,481	6,819,678	16,789,897
2014	Raw	36,689	1,890,289	6,672,558	17,011,370
	Cleaned	36,662	1,873,185	6,498,078	16,233,154
Across years	Raw	95,403	15,642,967	55,156,595	135,909,759
	Cleaned	95,310	15,491,554	53,720,820	130,442,122

Table A2: Comparison of Filtered and Remaining Household Sample (Shopping Preference)

Year	Sample	Households	Disc. share	PL share (Disc.)	PL share (Sup.)	Promo share
2006	Filtered	5421	39.1	28.4	6.4	18.1
	Remaining	21800	41.9	30.7	7.1	13.8
2007	Filtered	5421	39.4	27.6	6.6	20.6
	Remaining	19863	42.0	29.8	7.5	16.2
2008	Filtered	5421	41.1	28.5	7.2	22.0
	Remaining	19218	43.2	30.3	8.2	17.8
2009	Filtered	5421	41.5	28.1	7.3	24.2
	Remaining	19211	43.3	29.3	8.3	20.6
2010	Filtered	5421	41.5	27.5	7.6	25.8
	Remaining	28133	43.1	28.6	8.5	22.4
2011	Filtered	5421	41.1	27.3	7.9	27.1
	Remaining	29131	42.8	28.5	9.1	23.4
2012	Filtered	5421	41.4	27.6	8.3	28.2
	Remaining	32307	43.7	29.1	9.6	23.9
2013	Filtered	5421	41.4	27.6	8.4	29.6
	Remaining	31124	44.0	29.4	9.9	24.8
2014	Filtered	5421	40.9	27.6	8.7	28.9
	Remaining	31241	43.3	29.1	10.3	24.6
Across years	Filtered	5421	40.8	27.8	7.6	24.9
	Remaining	89889	43.1	29.3	8.9	21.5

Notes: Disc = discounter; Sup = supermarket; PL = private label; Promo = promotion.

Table A3: Comparison of Filtered and Remaining Household Sample (Demographics)

Source Sample	ConsumerScan Filtered	ConsumerScan Remaining	Destatis Microcensus
Year	2006	2006	2006
N	5,421	8,380	39,766,000
Age group		%	
< 25 years	.7	2.9	5.0
25 - 34 years	10.3	19.7	14.3
35 - 44 years	23.5	23.5	21.1
45 - 54 years	23.9	17.8	18.0
55 - 64 years	21.9	14.5	14.3
65+ years	19.7	21.6	27.2
Income group (monthly, net)	%		
< 500 €	.7	.9	2.6
500 - 1499 €	23.6	24.4	35.4
1500 - 1999 €	19.2	19.2	16.4
2000 - 3249* €	42.5	41.2	23.9
3250+** €	13.9	14.3	15.1
Other***	-	-	6.7
Household size	%		
1 person	21.9	22.3	38.8
2 persons	39.2	38.4	33.6
3 persons	18.2	18.4	13.5
4 persons	15.3	15.1	10.3
5+ persons	5.4	5.9	3.7
Number of children	%		
No children	78.6	72.9	68.8
1 child	11.3	14.1	16.6
2 children	8.1	10.1	11.4
3 children	1.8	2.4	2.9
4 children	.2	.4	.6
5+ children	.0	.1	.2

* Microcensus income group: 2000 - 3200 €
** Microcensus income group: 3250+ €
*** Households with at least one person being self-employed farmer, or information not available.

Appendix B: Variable Operationalization

We define 2006 as the initialization period t0.

Relative price index store format: The relative price index of store format j for household h at time t is calculated as:

$$\text{Rel.Price}_{jht} = \frac{\text{Price}_{jht}}{\sum_{j=1}^{J} \text{Price}_{jht}\ \text{ss}_{jht0}},$$

where Price_{jht} is the price of store format j for household h at time t relative to the average price of all formats ($\sum_{j=1}^{J} \text{Price}_{jht}$), weighted by household's h share of total spending in store format j (ss_{jht0}) from the initialization period t0. Note that j = 1 is the discount store format and j = 2 is the supermarket format. Then Price_{jht} is calculated as:

$$\text{Price}_{jht} = \sum_{c=1}^{C} \frac{\text{Price}_{jct}}{\text{Price}_{ct0}}\ \text{cs}_{hct0},$$

where Price_{jct} is the median price of category c in store format j at time t, Price_{ct0} is the sample median price of category c in the initialization period t0, and cs_{hct0} is the share of total spending by household h in the initialization period t0 in category c.

To reduce nomenclature clutter and reflect the fact that we need to include only the relative price index of j = 1 (discount store format) in our model, we name the corresponding variable PriceDisc_{ht} throughout the paper.

Relative price index brand type: The relative price index of brand type k for household h at time t is calculated as:

$$\text{Rel.Price}_{kht} = \frac{\text{Price}_{kht}}{\sum_{k=1}^{K} \text{Price}_{kht}\ \text{bs}_{kht0}},$$

where Price_{kht} is the price of brand type k for household h at time t relative to the average price of all brand types ($\sum_{k=1}^{K} \text{Price}_{kht}$), weighted by household's h share of total spending for brand type k (bs_{kht0}) from the initialization period t0. Note that brand type k is defined conditional on

store format j, and therefore, k = 1 is private label at discount store format, k = 2 is national brand at discount store format, k = 3 is private label at supermarket format, and k = 4 is national brand at supermarket format. Then $Price_{kht}$ is calculated as:

$$Price_{hkt} = \sum_{c=1}^{C} \frac{Price_{kct}}{Price_{ct0}} \, cs_{hct0},$$

where $Price_{kct}$ is the median price of category c for brand type k at time t, and $Price_{ct0}$ and cs_{hct0} are as defined previously.

To reduce nomenclature clutter and reflect the fact that we need to include only the relative price index of k = 1 (private label at discount store format) and k = 3 (private label at supermarket format) in our model, we name the corresponding variables $PricePLDisc_{ht}$ and $PricePLSup_{ht}$ throughout the paper.

Relative assortment size index store format: The relative assortment size index of store format j for household h at time t is calculated as:

$$Rel.AssrtSize_{jht} = \frac{AssrtSize_{jht}}{\sum_{j=1}^{J} AssrtSize_{jht} \, ss_{jht0}},$$

where $AssrtSize_{jht}$ is the assortment size of store format j for household h at time t relative to the weighted average assortment size of all store formats ($\sum_{j=1}^{J} AssrtSize_{jht} \, ss_{jht0}$), with weights ss_{jht0} as defined previously. Note that j = 1 is the discount store format and j = 2 is the supermarket format. Then $AssrtSize_{jht}$ is calculated as:

$$AssrtSize_{jht} = \sum_{c=1}^{C} AssrtSize_{jct} \, cs_{hct0},$$

where $AssrtSize_{jct}$ is the number of unique SKUs in category c of store format j at time t, and cs_{hct0} is as defined previously.

To reduce nomenclature clutter and reflect the fact that we need to include only the relative assortment size index of j = 1 (discount store format) in our model, we name the corresponding variable $AssrtDisc_{ht}$ throughout the paper.

Relative assortment size index brand type: The relative assortment size index of brand type k for household h at time t is calculated as:

$$\text{Rel.AssrtSize}_{kht}=\frac{\text{AssrtSize}_{kht}}{\sum_{k=1}^{K}\text{AssrtSize}_{kht}\ \text{bs}_{kht0}},$$

where AssrtSize_{kht} is the assortment size of brand type k for household h at time t relative to the weighted average assortment size of all brand types ($\sum_{k=1}^{K}\text{AssrtSize}_{kht}\ \text{bs}_{kht0}$), with weights bs_{kht0} and brand type k as defined previously. Note that brand type k is defined conditional on store format j, and therefore, k = 1 is private label at discount store format, k = 2 is national brand at discount store format, k = 3 is private label at supermarket format, and k = 4 is national brand at supermarket format. Then AssrtSize_{kht} is calculated as:

$$\text{AssrtSize}_{kht}=\sum_{c=1}^{C}\text{AssrtSize}_{kct}\ \text{cs}_{hct0},$$

where AssrtSize_{kct} is the number of unique SKUs of brand type k in category c j at time t, and cs_{hct0} is as defined previously.

To reduce nomenclature clutter and reflect the fact that we need to include only the relative assortment size index of k = 1 (private label at discount store format) and k = 3 (private label at supermarket format) in our model, we name the corresponding variables AssrtPLDisc_{ht} and AssrtPLSup_{ht} throughout the paper.

Relative price tier index: The relative index of price tier l for household h at time t is:

$$\text{Rel.PriceTier}_{lht}=\frac{\text{PriceTier}_{lht}}{\sum_{l=1}^{L}\text{PriceTier}_{lht}\ \text{ts}_{lht0}}$$

where PriceTier_{lht} is the number of unique SKUs for household h offered in price tier l at time t relative to the weighted average number of unique SKUs offered across all price tiers ($\sum_{l=1}^{L}\text{PriceTier}_{lht}\text{ts}_{lht0}$), weighted by household's h share of total spending on products offered in price tier l (ts_{lht0}) from the initialization period t0. Note that l = 1 is the promotional price

tier (i.e., temporary price reduction, coupon, free-pack, product add-on) and l = 2 is the regular price tier. Then $PriceTier_{lht}$ is calculated as:

$$PriceTier_{lht} = \sum_{c=1}^{C} PriceTier_{lct}\ cs_{hct0},$$

where $PriceTier_{lct}$ is the number of unique SKUs being offered in price tier l in category c at time t, and cs_{hct0} is as defined previously.

To reduce nomenclature clutter and reflect the fact that we need to include only the relative price tier index of l = 1 (promotional price tier) in our model, we name the corresponding variable $PricePromo_{ht}$ throughout the paper.

Relative advertising index store format: The relative advertising index of store format j for household h at time t is calculated as:

$$Rel.Adv_{jht} = \frac{Adv_{jt}}{\sum_{j=1}^{J} Adv_{jht}\ ss_{jht0}},$$

where Adv_{jht} is the advertising spending, cumulative over store format j at time t relative to the average advertising spending across all store formats ($\sum_{j=1}^{J} Adv_{jt}$), weighted by household's h share of total spending in store format j (ss_{jht0}) from the initialization period t0. Note that j = 1 is discount store format and j = 2 is supermarket format.

To reduce nomenclature clutter and reflect the fact that we need to include only the relative advertising index of j = 1 discount store format) in our model, we name the corresponding variable $AdvDisc_{ht}$ throughout the paper.

Relative advertising index brand type: The relative price index of brand type k for household h at time t is calculated as:

$$Rel.Adv_{kht} = \frac{Adv_{kt}}{\sum_{k=1}^{K} Adv_{kht}\ bs_{kht0}},$$

where Adv_{kht} is the advertising spending, cumulative over brand type k at time t relative to the average advertising spending across brand types ($\sum_{k=1}^{K} Adv_{kt}$), weighted by household's h share

of total spending on brand type k (bs_{kht0}) from the initialization period t0. Note that k = 1 is private label and k = 2 is national brand.

To reduce nomenclature clutter and reflect the fact that we need to include only the relative advertising index of k = 1 private label) in our model, we name the corresponding variable $AdvPL_{ht}$ throughout the paper.

Appendix C: Model Results

Table C1: Initial Shopping Strategy Assignment

Initial Strategy	Variable	Coef.	SE	Z-value		Wald(0)		DF
1	Intercept	.268	.179	1.494		486.054	***	6
2	Intercept	.190	.175	1.085				
3	Intercept	.300	.279	1.074				
4	Intercept	2.375	.127	18.759	***			
5	Intercept	-.462	.230	-2.007	**			
6	Intercept	-2.247	.524	-4.289	***			
7	Intercept	-.423	.275	-1.536				
1	Income	-.023	.149	-.152		8.909		6
2	Income	-.011	.165	-.064				
3	Income	.052	.179	.290				
4	Income	.165	.105	1.571				
5	Income	-.517	.211	-2.447	**			
6	Income	.155	.351	.442				
7	Income	.179	.185	.966				
1	HHSize	.084	.238	.355		12.985	**	6
2	HHSize	.155	.252	.614				
3	HHSize	.035	.273	.127				
4	HHSize	.609	.177	3.443	***			
5	HHSize	.046	.301	.153				
6	HHSize	-1.252	.738	-1.697	*			
7	HHSize	.323	.281	1.148				
1	Kids	.071	.240	.296		6.470		6
2	Kids	-.172	.262	-.656				
3	Kids	-.845	.517	-1.634				
4	Kids	-.126	.180	-.697				
5	Kids	-.283	.380	-.745				
6	Kids	1.220	.653	1.868	*			
7	Kids	.135	.282	.479				
1	Age	-.037	.142	-.262		7.708		6
2	Age	-.091	.154	-.593				
3	Age	-.360	.169	-2.132	**			
4	Age	.169	.106	1.599				
5	Age	-.019	.157	-.120				
6	Age	.130	.314	.415				
7	Age	.208	.190	1.094				
1	Factor	.759	.154	4.930	***	54.215	***	6
2	Factor	.065	.183	.354				
3	Factor	.142	.193	.735				
4	Factor	.106	.119	.887				
5	Factor	.023	.205	.113				
6	Factor	.377	.380	0.994				
7	Factor	-1.472	.234	-6.284	***			

Notes: ***$p < .01$; **$p < .05$; *$p < .1$.
Coef = coefficient; SE = standard error; DF = degrees of freedom.

Table C2: State-Dependent Effects on Discounter Share

Dependent variable (DV) = Discounter share (DiscSOW)											
Strat.	**Variable**	**Coef.**	**SE**	**Z**		**Wald(0)**		**DF**	**Wald(=)**		**DF**
	Intercept	39.178	.155	253.000	***	64009.098	***	1			
	State 1	24.096	.305	78.893	***	14958.757	***	6			
	State 2	-7.988	.329	-24.274	***						
	State 3	-12.967	.330	-39.268	***						
	State 4	.714	.170	4.198	***						
	State 5	22.666	.312	72.566	***						
	State 6	-15.938	.638	-24.970	***						
	State 7	-10.582	.324	-32.673	***						
1	PriceDisc	1.088	.481	2.263	**	210.255	***	7	10.929	*	6
2	PriceDisc	1.998	.415	4.809	***						
3	PriceDisc	2.601	.406	6.408	***						
4	PriceDisc	1.667	.184	9.059	***						
5	PriceDisc	2.317	.682	3.395	***						
6	PriceDisc	3.345	.848	3.943	***						
7	PriceDisc	2.055	.453	4.538	***						
1	AssrtDisc	2.311	.468	4.938	***	46.608	***	7	32.375	***	6
2	AssrtDisc	.368	.445	.826							
3	AssrtDisc	.064	.415	.155							
4	AssrtDisc	.226	.193	1.171							
5	AssrtDisc	.015	.677	.022							
6	AssrtDisc	-1.409	.912	-1.546							
7	AssrtDisc	1.961	.477	4.113	***						
1	AdvDisc	-.117	.226	-.516		8.217		7	5.702		6
2	AdvDisc	-.034	.159	-.216							
3	AdvDisc	-.043	.155	-.276							
4	AdvDisc	-.142	.069	-2.052	**						
5	AdvDisc	-.584	.325	-1.795	*						
6	AdvDisc	.366	.418	.875							
7	AdvDisc	.097	.161	.603							
1	DV (lag)	11.145	.233	47.867	***	46456.436	***	7	4899.195	***	6
2	DV (lag)	16.688	.342	48.787	***						
3	DV (lag)	11.662	.311	37.552	***						
4	DV (lag)	23.812	.125	189.890	***						
5	DV (lag)	16.211	.350	46.260	***						
6	DV (lag)	9.748	.607	16.063	***						
7	DV (lag)	11.115	.307	36.245	***						
	Quarter 1	.382	.122	3.138	***	51.263	***	3			
	Quarter 2	.450	.121	3.732	***						
	Quarter 3	-.049	.119	-.412							
	Quarter 4	-.783	.119	-6.577	***						

Notes: ***$p < .01$; **$p < .05$; *$p < .1$.
Coef = coefficient; SE = standard error; DF = degrees of freedom.

Table C3: State-Dependent Effects on Private Label Share (Discounter)

Dependent variable (DV) = PL share in discounter (PLDiscSOW)											
Strat.	**Variable**	**Coef.**	**SE**	**Z**		**Wald(0)**		**DF**	**Wald(=)**		**DF**
	Intercept	25.285	.123	206.259	***	42542.772	***	1			
	State 1	26.622	.258	103.183	***	11716.906	***	6			
	State 2	-4.042	.256	-15.769	***						
	State 3	-6.623	.256	-25.862	***						
	State 4	1.235	.135	9.175	***						
	State 5	-1.597	.239	-6.688	***						
	State 6	-8.502	.524	-16.227	***						
	State 7	-7.094	.244	-29.125	***						
1	PricePLDisc	2.326	.221	10.508	***	503.559	***	7	35.350	***	6
2	PricePLDisc	1.554	.263	5.917	***						
3	PricePLDisc	2.584	.266	9.717	***						
4	PricePLDisc	1.393	.115	12.077	***						
5	PricePLDisc	2.237	.319	7.018	***						
6	PricePLDisc	3.013	.599	5.032	***						
7	PricePLDisc	1.330	.274	4.860	***						
1	AssrtPLDisc	.344	.224	1.535		55.734	***	7	39.786	***	6
2	AssrtPLDisc	.469	.269	1.742	*						
3	AssrtPLDisc	.278	.265	1.049							
4	AssrtPLDisc	.210	.110	1.911	*						
5	AssrtPLDisc	-.464	.275	-1.691	*						
6	AssrtPLDisc	-1.154	.578	-1.997	**						
7	AssrtPLDisc	1.681	.278	6.043	***						
1	AdvPL	.340	.108	3.151	***	15.863	**	7	10.290		6
2	AdvPL	.203	.146	1.394							
3	AdvPL	.148	.155	.956							
4	AdvPL	.073	.061	1.189							
5	AdvPL	-.120	.199	-.604							
6	AdvPL	-.037	.348	-.108							
7	AdvPL	-.172	.152	-1.132							
1	DV (lagged)	11.201	.179	62.451	***	43244.400	***	7	3812.236	***	6
2	DV (lagged)	13.651	.283	48.186	***						
3	DV (lagged)	9.028	.246	36.642	***						
4	DV (lagged)	18.861	.109	173.103	***						
5	DV (lagged)	12.163	.249	48.932	***						
6	DV (lagged)	8.348	.570	14.635	***						
7	DV (lagged)	8.478	.252	33.636	***						
	Quarter 1	.648	.097	6.695	***	130.487	***	3			
	Quarter 2	.350	.097	3.590	***						
	Quarter 3	.037	.096	.381							
	Quarter 4	-.783	.119	-6.577	***						

Notes: ***$p < .01$; **$p < .05$; *$p < .1$.
Coef = coefficient; SE = standard error; DF = degrees of freedom.

Table C4: State-Dependent Effects on Private Label Share (Supermarket)

Dependent variable (DV) = PL share in supermarkets (PLSupSOW)											
Strat.	**Variable**	**Coef.**	**SE**	**Z**		**Wald(0)**		**DF**	**Wald(=)**		**DF**
	Intercept	11.699	.077	151.922	***	23080.312	***	1			
	State 1	-7.186	.115	-62.660	***	9282.809	***	6			
	State 2	6.785	.120	56.531	***						
	State 3	-6.087	.112	-54.262	***						
	State 4	-3.980	.075	-52.901	***						
	State 5	-7.466	.120	-62.345	***						
	State 6	23.886	.303	78.811	***						
	State 7	-5.952	.113	-52.684	***						
1	PricePLSup	-.195	.092	-2.111	**	16.939	**	7	16.035	**	6
2	PricePLSup	-.143	.190	-.751							
3	PricePLSup	.050	.126	.400							
4	PricePLSup	-.086	.051	-1.695	*						
5	PricePLSup	.056	.129	.432							
6	PricePLSup	-.185	.403	-.459							
7	PricePLSup	.375	.125	2.991	***						
1	AssrtSup	-.058	.086	-.675		74.896	***	7	71.240	***	6
2	AssrtSup	1.149	.197	5.825	***						
3	AssrtSup	.328	.127	2.589	***						
4	AssrtSup	.133	.051	2.625	***						
5	AssrtSup	-.120	.113	-1.065							
6	AssrtSup	2.782	.368	7.568	***						
7	AssrtSup	-.119	.126	-.947							
1	AdvPL	-.029	.055	-.529		7.288		7	7.213		6
2	AdvPL	-.052	.118	-.438							
3	AdvPL	-.202	.099	-2.050	**						
4	AdvPL	.015	.037	.403							
5	AdvPL	.011	.095	.116							
6	AdvPL	-.352	.253	-1.393							
7	AdvPL	.084	.090	.935							
1	DV (lagged)	2.873	.102	28.163	***	29682.669	***	7	6563.606	***	6
2	DV (lagged)	8.621	.090	96.223	***						
3	DV (lagged)	3.980	.088	45.203	***						
4	DV (lagged)	7.631	.048	158.300	***						
5	DV (lagged)	2.044	.130	15.714	***						
6	DV (lagged)	9.400	.243	38.694	***						
7	DV (lagged)	3.397	.116	29.403	***						
	Quarter 1	.052	.043	1.195		2.131		3			
	Quarter 2	-.040	.043	-.928							
	Quarter 3	.017	.043	.398							
	Quarter 4	-.029	.043	-.673							

Notes: ***$p < .01$; **$p < .05$; *$p < .1$.
Coef = coefficient; SE = standard error; DF = degrees of freedom.

Table C5: State-Dependent Effects on Promotion Share

Dependent variable (DV) = Promotion share (PromoSOW)											
Strat.	**Variable**	**Coef.**	**SE**	**Z**		**Wald(0)**		**DF**	**Wald(=)**		**DF**
	Intercept	24.833	.136	182.176	***	33187.946	***	1			
	State 1	-9.033	.241	-37.459	***	6864.709	***	6			
	State 2	-2.795	.255	-10.951	***						
	State 3	-8.791	.272	-32.332	***						
	State 4	.681	.158	4.304	***						
	State 5	5.250	.303	17.354	***						
	State 6	-7.578	.538	-14.090	***						
	State 7	22.266	.353	63.058	***						
1	PricePromo	1.287	.209	6.147	***	778.307	***	7	167.157	***	6
2	PricePromo	1.896	.272	6.970	***						
3	PricePromo	.904	.274	3.304	***						
4	PricePromo	1.757	.118	14.850	***						
5	PricePromo	4.875	.330	14.779	***						
6	PricePromo	1.181	.685	1.724	*						
7	PricePromo	4.267	.327	13.035	***						
1	DV (lagged)	9.936	.247	40.207	***	28912.398	***	7	1639.597	***	6
2	DV (lagged)	13.940	.275	50.768	***						
3	DV (lagged)	8.810	.299	29.498	***						
4	DV (lagged)	17.410	.131	133.216	***						
5	DV (lagged)	13.851	.306	45.315	***						
6	DV (lagged)	8.732	.613	14.238	***						
7	DV (lagged)	8.122	.288	28.167	***						
	Quarter 1	-.014	.112	-.127		119.050	***	3			
	Quarter 2	-1.104	.112	-9.834	***						
	Quarter 3	.318	.112	2.841	***						
	Quarter 4	.800	.111	7.192	***						

Notes: ***$p < .01$; **$p < .05$; *$p < .1$.
Coef = coefficient; SE = standard error; DF = degrees of freedom.

Paper III

Ratings, Reviews, and Recessions: How Business Cycles Shape Online Opinion

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Abstract

Existing research demonstrates the extensive impact macroeconomic conditions have on consumer purchase behavior. Despite this apparently far-reaching influence, insights beyond consumers' purchase decision remain sparse. However, expressing ones opinion about products through ratings and reviews nowadays constitutes an integral part of the buying process itself. Therefore, the author investigates in this study whether and how economic expansions and contractions affect online opinion and provides different theoretical explanations for potential effects. Relying on a longitudinal data set of online product reviews from the online retailer Amazon.com, the author shows that numeric ratings and review sentiment are negatively affected by economic expansions while review sentiment also is positively affected by economic contractions. These findings are in line with expectation-disconfirmation theory. Additionally, the negative effect of economic expansions is particularly severe for popular product, i.e., those with a high number of evaluations.

Keywords: Online opinion, online product reviews, business cycles

1 Introduction

During economic downturns, consumers tend to behave differently from those experiencing economic upswings (Ang, Leone, and Kotler 2000; Dutt and Padmanabhan 2011). And the US economy has gone through some particularly severe ups and downs in the past two decades considering the early 2000s recession or the Great Recession from 2007 to 2009. Prior research has proven a far-reaching impact of changing economic conditions on consumers, in particular on their behavior prior to and during purchase. Thus, crisis-hit consumers, for instance, demonstrate higher price knowledge (Estelami, Lehmann, and Holden 2001) and exercise more purchase planning (Hampson and McGoldrick 2013). They also tend to reduce or postpone purchases altogether in categories like durables (e.g., Deleersnyder et al. 2004; Dutt and Padmanabhan 2011) or non-essential goods and services (e.g., Kamakura and Du 2012) until economic prosperity returns. In other product categories, consumers reallocate their spending towards more affordable brand types (e.g., Dubé, Hitsch, and Rossi 2018; Lamey et al. 2007), store formats (Lamey 2014), or items being offered on temporary price reductions (Cha, Chintagunta, and Dhar 2015; Ma et al. 2011).

However, despite the apparently far-reaching impact of business cycles on consumer behavior, their importance for and impact on consumers' postpurchase behavior has been widely neglected. Only recently, researchers started to link macroeconomic variables with post-purchase outcomes like consumer satisfaction. (e.g., Fornell, Rust, and Dekimpe 1996; Yeung et al. 2013). These insights yet are, with one exception provided by Hunneman, Verhoef, and Sloot (2015), limited to the aggregated economic level and therefore disregard individual attributes of the focal object of interest (e.g., households, stores, or products). One reason for the lack of individual level analyses may be the absence of individual and longitudinal consumer satisfaction data. Survey-based measures, as often used in the general satisfaction literature, are normally limited to a relatively short time horizon. A direct measure of consumer

satisfaction with a purchase, however, that is highly disaggregate, available for long time horizons, and easily obtainable, is consumers' online opinion represented in the numeric rating and review sentiment of online product reviews.

There is a fair amount of agreement among researchers, practitioners, and consumers that online opinions are of particular relevance for both (potential) buyers as well as suppliers. Potential buyers use online opinions regularly to learn about the quality of products (Zhao et al. 2013), ultimately striving to reduce uncertainty about their purchase by identifying products that best match their individual usage conditions (Chen and Xie 2008). For suppliers on the other side, online opinions are important because they may impact sales (Chevalier and Mayzlin 2006, Chintagunta, Gopinath, and Venkataraman 2010) and are used by marketers to enrich marketing strategy (Chen and Xie 2008; Cui, Lui, and Guo 2012).

Around 20% of consumers submit their own online opinion for the majority of their online purchases (Pilon 2016). Thereby, they communicate their own opinion regarding experienced product performance (De Langhe, Fernbach, and Lichtenstein 2016) and resulting (dis-)satisfaction with their purchase. Prior research on online opinion formation, however, has demonstrated that such assessments are not a solely rational process. There is extensive evidence for temporal, sequential, and social dynamics that bias how consumers evaluate products they have purchased (e.g., Godes and Silva 2012, Moe and Trusov 2011). Nevertheless, existing research in this domain has limited its scope to influences within an opinion platform's prevailing rating environment (e.g., heterogeneity among previous opinions) and reviewers' characteristics (e.g., motivation to submit an opinion). Potential factors being exogenous to the focal platform have not been considered so far.

At this point, we see a fruitful avenue to combine the streams of research on business cycles in marketing and online opinion formation to contribute to both of them in a unique way. First, we address the gap in the business cycle literature and link macroeconomic changes to

consumers' postpurchase behaviors. We do so by incorporating online opinion as a direct representation of individual purchase satisfaction and investigate how economic expansions and contractions may affect consumers' satisfaction with a purchase. Knowledge about systematic shifts in how consumers rate and review their purchases conditional on economic phases is indeed important. Economic downturns, for example, may have a negative impact on product demand. Assuming a case in which consumers also rate and review products systematically more negative during economic downturns, would then even lead to an acceleration of declining sales, because lower ratings lead to lower sales (e.g., Chevalier and Mayzlin 2006). Even though marketers may not be able to prevent such economic fluctuations from happening, they can, to some extent, limit the impact they have on firm performance. In the aforementioned case, marketers may, for instance, consider to run electronic word of mouth campaigns to counteract declining ratings and reviews.

Beyond that, and given the disaggregate nature of our data, we are also able to consider an important product characteristic - product popularity - as potentially moderating factor of the business cycle-online opinion relationship. Popular products may be more intensively exposed to such business cycle effects, in either a positive or a negative way. Popular products appear in leading ranking positions and thus are more visible in the market. Consequently, they exhibit increased awareness from potential buyers, are ultimately purchased more often compared to unpopular products, and thereby accumulate more product evaluations. Thus, popular products provide more information for potential buyers which may lead to better purchase decisions and, for instance, an attenuation of potentially negative business cycle effects. However, consumers may also be influenced to make a purchase by the mere popularity of a product and neglect the more on information popular products offer. This may lead to worse purchase decisions and, for instance, an amplification of negative business cycle effects. Knowledge about such effects would allow marketers to consider preventive marketing actions.

We therefore see product popularity as a viable characteristics that may amplify or attenuate the impact of business cycles on online opinion.

Second, we extend research on online opinion formation by considering potential drivers of online opinions that are exogenous to the focal review platform. Thereby, we acknowledge both numeric ratings and review sentiment, i.e., the positivity or negativity in the textual component of a review, being important measures of online opinion, something that has been widely neglected to date. Previous research has shown that the total information embedded in online product reviews cannot be captured by a single numeric value (Archak, Ghose, and Ipeirotis 2011). Online product reviews rather are multifaceted and the textual component is an important determinant, e.g., of future consumers' choice over and above numeric ratings. Therefore, we argue that review sentiment may also be more sensitive in capturing potential shifts of consumer satisfaction. In conclusion, we pursue two foundational research objectives:

- Investigate how economic expansions and contractions impact numeric ratings and review sentiment in online product reviews.
- Determine the moderating role of product popularity in the business cycle-online opinion relationship.

To do so, we rely on an extensive data set containing book reviews from the online retailer Amazon.com. Covering almost two decades, the longitudinal characteristics of this data allow to capture the potential effects of multiple business cycles. We complement the review data with macroeconomic information from the US Bureau of Economic Analysis (BEA) and construct a semi-dummy variable to represent both different phases of a business cycle and their respective magnitudes.

Our results reveal that economic expansions and contractions indeed have apparent and distinct effects on numeric ratings and review sentiment in online product reviews. Whereas economics contractions show a positive effect on review sentiment, economic expansions

exhibit a negative effect on both numeric ratings and review sentiment. We propose these effects being the result of increasing consumer expectations during economic expansions and a subsequent higher likelihood for a negative disconfirmation. Furthermore, the negative effects tend to amplify with product popularity.

In the next section, we review relevant literature from the research stream on business cycles in marketing and online opinion formation. After specifying our data bases and model formulations, we describe and discuss our results in order of the formulated research questions. We conclude with some managerial implications for retailers and manufacturers, or in case of our focal product category publishers, and provide directions for future research.

2 Literature Review

This study combines two different streams in the marketing research literature which have not been combined so far. First, we refer to work on the impact of business cycles, which has received considerable attention following the Great Recession. This literature stream considers in particular the effect of business cycles on marketing strategy, marketing effectiveness, and marketing performance.[1] Second, we consider literature on online consumer reviews. This literature stream investigates both the antecedents of reviewing behavior as well as the consequences of aggregate review characteristics on company performance.

2.1 Business Cycles and Marketing

Our study ties into the business cycle literature focusing on marketing performance. Most studies in this domain link economic fluctuations to various purchase related performance outcomes, predominantly in an offline retailing or service context. Therein, some studies focus on how consumers economize their total spending in the face of macroeconomic changes on

[1] See Dekimpe and Deleersnyder (2017) for an extensive literature review on business cycles in marketing.

consumer durables (Deleersnyder et al. 2004), traveling (Dekimpe, Peers, and Van Heerde 2016), or movie attendance (Dhar and Weinberg 2016). Other studies rather focus on consumers' reallocation of monetary resources across various product categories such as durables, non-durables, and services (Dutt and Padmanabhan 2011), or (non-)positional goods/services (Kamakura and Du 2012). Similarly, some studies demonstrate how consumers shift budgets between brand types (Dubé, Hitsch, and Rossi 2018; Lamey et al. 2007) or store formats (Lamey 2014) within a given category or industry.

While quite some attention has been given to the relationship between business cycles and consumer purchase behavior, subsequent postpurchase behaviors and attitudes have been widely neglected. Moreover, those few studies that consider, e.g., consumers' satisfaction judgments regarding products, services, or stores, almost exclusively assess the contribution of satisfaction to future demand across varying economic conditions. The preceding effect of varying economic conditions on consumers' satisfaction judgements remains a rather untouched field of research. Fornell, Rust, and Dekimpe (2010), for instance, demonstrate on an aggregate level that changes in consumer satisfaction have a significant impact on spending growth. This impact, however, does not change in times of economic turmoil such as the financial and housing crisis that took place between 2006 and 2008. Yeung et al. (2013) come to a similar conclusion. Using country-level per capita income as a continuous measure for economic performance, the authors find the relationship between consumer satisfaction and consumer expenditures to be unaffected by economic changes. While these findings have been based on aggregate data, only few other studies turn towards individual-level information. Using consumer-level survey and transaction data and an aggregate continuous measure of perceived economic wellbeing, Kumar et al. (2014) find satisfaction with service offerings to matter more for consumer purchase behavior when the economy is doing better and not worse. The only study, so far, considering changing economic conditions not only to be a moderating

factor of the satisfaction-demand relationship but also a direct influencing factor on consumer satisfaction is the study by Hunneman, Verhoef, and Sloot (2015). Using consumer-level survey information, the authors investigate the relationship between consumers' individual economic confidence and their satisfaction with retailers in the context of grocery shopping. Although the authors show that the relationship between service attributes and consumer satisfaction is stronger when consumer confidence is low, a direct effect of consumer confidence on store satisfaction has not been found.

In this regard, we follow a recent call by Dekimpe and Deleersnyder (2017) to broaden the scope of existing research questions in the business cycle literature and contribute to this stream of research in four ways. First, we establish online opinion expressed through online product reviews to be a meaningful measure for consumer satisfaction. While previous research on satisfaction in the business cycle literature relies on survey-based satisfaction measures, we utilize online reviews as a behavioral expression of satisfaction towards a concrete target object, a specific product. Second, we propose business cycles to be a direct influencing factor of consumer satisfaction outcomes. While the moderating role of business cycles on the satisfaction-demand relationship has drawn some attention so far (e.g., Fornell, Rust, and Dekimpe 2010; Hunneman, Verhoef, and Sloot 2015; Kumar et al. 2014; Yeung et al. 2013), a potential preceding effect of business cycles on satisfaction has been widely neglected. We address this research gap and test competing mechanisms for potential effects. Third, we consider product popularity as an important characteristic that may accelerate or amplify the impact business cycles have on consumers' satisfaction with a product. So far, such individual characteristics have been widely neglected in research on the business cycle-satisfaction link. Only Hunneman, Verhoef, and Sloot (2015) provide a similar setting and investigate how changes in the economic environment affect the relationship between store attributes (i.e., service, price, and convenience) and consumer satisfaction. Fourth, we deepen the

understanding of asymmetries over the business cycle by separately considering the existence and magnitude of different business cycle phases. Previous studies on satisfaction in the context of business cycles have either used as single continuous economic variable (Hunneman, Verhoef, and Sloot 2015; Kumar et al. 2014; Yeung et al. 2013) allowing to capture the magnitude of economic performance or a dummy economic variable (Fornell, Rust, and Dekimpe 2010) allowing to capture the existence of different business cycle phases. By constructing a continuous semi-dummy economic variable for economic expansions and contractions we capture both the existence of different business cycle phases as well as their individual magnitudes. Therefore, we are able to draw a clearer picture of the underlying mechanisms during economic expansions and contractions. Fifth, we meet the request by Dekimpe and Deleersnyder (2017) for longer time spans and lower data aggregation by evaluating online opinion on individual level and over multiple economic expansion and contraction periods.

2.2 Online Opinion Formation

The literature stream on online opinion formation can be divided into domains investigating either the antecedents or consequences of online consumer reviews and ratings. While studies in the latter domain have consistently shown online opinion to have an impact on sales, some disagreement exists about which particular dimension of online opinion constitutes the main driver. Whereas some studies document the volume of online reviews to predominantly predict sales (e.g., Duan, Gu, and Whinston 2008; Gu, Park, and Konana 2012; Ho-Dac, Carson, and Moore 2014; Liu 2006), other studies attribute the valence (e.g., Chavalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman. 2010; Dellarocas, Zhang, and Awad 2007) or variance (e.g., Sun 2012) of online reviews to be the main predictor.

Yet this study ties into the research domain on antecedents of online product reviews which mainly focuses on various influences unrelated to consumers' objective product assessments that structurally bias their rating behavior. Earlier work in this area has considered social influences as one potential driver of consumer rating behavior. Schlosser (2005) demonstrates that consumers tend to negatively adjust their own posted opinion about a product after reading others' negative opinions about that product, predominantly to differentiate themselves from the existing opinions. Moe and Trusov (2011) support this notion of a negative differentiation behavior. Additionally, the authors provide evidence that disagreement among raters, as indicated by the rating variance, discourages from posting extreme positive or negative opinions, as well as that ratings decrease with increasing volume of incoming ratings. The dynamic trends of incoming ratings have also been of particular interest in other studies. As such, Li and Hitt (2008) document a negative trend of rating valence over the time a product is on the market. The authors argue this trend to emerge due to a self-selection bias in which early buyers with significantly different tastes and preferences towards the product generate more favorable ratings than later buyers. Wu and Huberman (2008) argue this negative trend rather to emerge with the sequential order of incoming ratings. The authors explain that, given that submitting a review is costly in terms of time and effort, disagreeing opinions are overrepresented with increasing rating volume because they have a greater impact on the oftentimes prevailing high rating average and thus are worth the costs. Godes and Silva (2012) build up on these two arguments and suggest alternative explanations. Considering both temporal and sequential dynamics they show that both constitute simultaneously occurring but distinct dynamic processes. The dissimilarity among reviewers surges with the sequence of incoming ratings. This leads to increased difficulties for consumers to assess relevant reviews for their purchase decision, causing more purchase failure and thus lower ratings. More importantly, the authors demonstrate the negative temporal dynamics to be rather associated

with calendar time than the time of a product on the market. The authors state that "there may be an overall economy-wide drop in consumers' ratings of products." But whether this effect is driven by "the macroeconomic environment, or some other factor(s)" remains an open question.

Thus, we contribute to the literature on online opinion formation in two ways. First and foremost, we follow the call of Godes and Silva (2012) and deepen insights on the influencing factors of online opinion. While previous studies in this regard take a rather local perspective and consider only what is happening on the opinion platform itself (i.e., dynamic trends, reviewer or review environment characteristics), we extend this work and establish the general macroeconomic environment to be an important global influencing factor in consumers' online opinion formation. Second, previous studies on online opinion formation focus only on the numerical rating component and neglect the textual component of online reviews. However, previous research has shown that the total information embedded in online reviews cannot be captured by the numeric rating alone (Archak, Ghose, and Ipeirotis 2011). Moreover, the sentiment in review text has been shown to be less extreme than the numerical ratings (Schoenmüller et al. 2018). Thus, the sentiment in the textual review component may potentially be considered to better capture the true satisfaction judgement of a consumer and be less prone to extreme evaluations caused by the construction of the discrete rating scale. Therefore, we consider both components to capture potential differences.

3 Theoretical Framework

Previous research on the antecedents and consequences of online opinion has mostly regarded online consumer ratings as representations of a product's true quality (Hu et al. 2006; Moe and Trusov 2011). Only recently studies have come to the conclusion that ratings do not necessarily reflect products' true quality (Hu, Pavlou, and Zhang 2017; De Langhe et al. 2016) but rather represent an expression of consumers' satisfaction with a product (Moon et al. 2010;

Mattwick and Mosteller 2017). This notion is in line with existing definitions of consumer satisfaction as a post-choice evaluative judgment concerning a specific purchase decision (Day 1984).

The subject of consumer satisfaction has been of great interest for researchers since several decades. Its long-term effects on, for instance, consumer loyalty and profitability are well documented (Anderson, Fornell, and Lehmann 1994; Anderson, Fornell, and Rust 1997; Anderson and Sullivan 1993; Bearden and Teel 1983; Bolton and Drew 1991; Fornell 1992; LaBarbera and Mazursky 1983; Oliver 1980; Oliver and Swan 1989a, b; Rust, Moorman, and Dickson 2002; Rust and Zahorik 1993). Previous research has also extensively looked into the underlying mechanisms that lead to consumer satisfaction. Thereby, both cognitive and affective components have been considered to constitute relevant predictors of consumers' satisfaction judgements (Szymanski and Henard 2001). The influence of cognition has primarily been studied in the context of what is known as disconfirmation paradigm (e.g., Bearden and Teel 1983; LaBarbera and Mazursky 1983; Oliver 1980; Oliver and DeSarbo 1988). Therein, consumers' expectations are conceptualized as the standard against which performance outcomes are evaluated. Contrarily, other studies have recognized that affect experienced during or before the consumption process, like happiness or disgust, may be a further predictor of consumers' satisfaction judgements (Westbrook 1987; Westbrook and Oliver 1991; Mano and Oliver 1993; Oliver 1993). Relying on the research stream on consumer satisfaction formation and literature from the field of behavioral economics, we provide in the following two distinct and competing explanations for potential effects of the macroeconomic environment on online opinion.

3.1 The Intrapersonal Affective Influence Explanation

Satisfaction results in part from consumers' evaluation of affect, i.e., emotions like joy, excitement, pride, anger, sadness, or guilt. It is an evaluative response comprising the affective element elicited during or before the consumption process which is then integrated into consumers' satisfaction assessment (Westbrook and Oliver 1991). Westbrook (1980) argues that, if comprising an affective element, this evaluative response may be influenced by other, more general states of affect as well. The affective states experienced by the consumer may not necessarily relate to the consumption object or process and vary with regard to their permanence and domain. Some affective states are relatively more permanent whereas others exhibit temporal dependency. Similarly, some affective states are particularly general in focus whereas others are limited to specific domains, like consumption activities. The group of relatively stable and more general affective influences comprise basic personality dispositions as well as enduring global attitude structures. Optimism/pessimism (Goldman-Eisler 1960, Tiger 1979) and happiness (Cantril 1965) constitute the former, life satisfaction (Andrews and Withey 1976) the latter.

Optimism, pessimism, and overall life satisfaction have attracted considerable attention in the behavioral economics literature. In particular, consumers have been shown to be more pessimistic (Katona 1975, p. 155) and less satisfied with their overall life (Hurd and Rohwedder 2010) during economic contractions than during expansions. Drawing on the intrapersonal affective influence explanation by Westbrook (1980), one could argue that business cycles systematically change consumers' intrapersonal affective states (i.e., optimism, pessimism, and overall life satisfaction) and thus have a direct effect on consumers' satisfaction judgements. In particular, the presence of negative affect induced by economic contractions may shape the affect evoked during the evaluation process inherent in satisfaction judgment of products consumers buy, leading to more unfavorable judgements. Equivalently, the positive affect

induced by economic expansions may lead to more favorable satisfaction judgements. As a result, we would expect economic contractions to have a negative effect and economic expansions to have a positive effect on online opinion as expression of consumer satisfaction.

3.2 The Expectation-Disconfirmation Explanation

Cognition as potential predictor of consumer satisfaction has been primarily studied in terms of the expectation-disconfirmation paradigm. Therein, expectations are considered as "pretrial beliefs about the product" (Olson and Dover 1979) which constitute a point of comparative reference. Thus, consumers form expectations regarding product performance in the prepurchase phase and compare them with experienced product performance in the subsequent postpurchase phase. Hence, consumers are satisfied when the performance exceeds their expectations (positive disconfirmation) and dissatisfied when the performance falls behind their expectations (negative disconfirmation). Thus consumer (dis-)satisfaction is directly influenced by the positive or negative disconfirmation of existing expectations regarding product performance. (Anderson 1973; Bearden and Teel 1983; LaBarbera and Mazurky 1983; Oliver 1980; Oliver 1981; Oliver and DeSarbo 1988, Olson and Dover 1979).

The behavioral economics literature recognizes expectations to be an integral part of consumer confidence (Kantona 1957; Kantona 1968). Consumer confidence refers to consumers' subjective expectations of their individual financial situation as well as the general economic climate (Katona 1968). Katona (1975, p. 155) argues that economic expansions increase consumer confidence. This, in turn, drives consumers' wants and aspirations for new and better products. One could argue that raising expectations due to economic prosperity may increase product expectations as well. At the same time, this upward shift in expectations increases the likelihood for negative disconfirmation when product performance remains unchanged. Thus, the increasing negative discrepancy between expectations and performance

may lead to unfavorable satisfaction judgements. Equivalently, lower consumer confidence during economic contractions diminishes consumers' wants and aspirations for new and better products. Thus, low expectations are more likely to be positively disconfirmed, leading to more favorable satisfaction judgements. In conclusion, we would expect economic contractions to have a positive effect and economic expansions to have a negative effect on online opinion.

4 Methodology

4.1 Research Context and Data

Our empirical analysis uses online product reviews gathered from the online retailer Amazon.com which are made available through the Stanford Network Analytics Project (He and McAuley 2016). Accounting for roughly one quarter of the online retail market, Amazon.com is the dominant e-commerce platform in the U.S. (Hadad 2017) and one of the largest accumulations of online opinions on the Internet. The available data set covers over 82 million product reviews across multiple product categories and spans a time frame from 1996 to 2014. For each review, there are unique product and reviewer identifiers available as well as the star rating, the review text (including a review summary), the product category, and the posting date.

We focus on one specific product category within our analysis, namely books, for several reasons. First, the books category has been extensively used in previous research on the antecedents of online opinion (Li and Hitt 2008; Wu and Huberman 2008, Godes and Silva 2012), which allows us to verify the consistency of our findings. Second, it is the top category in terms of number of available products, number of product reviews, and the category being available for the longest time on Amazon.com. As such, the books category accounts for over 27% of the available data set and covers the complete time span with the earliest reviews being from 1996 and the latest being from 2014. This long time period makes it particularly suitable

to capture the potential effects of multiple business cycles. Third, and most important, the books category exhibits specific characteristics that rule out potential sources of noise. One such source of noise that may be crucial for consumers' (dis-)satisfaction judgement is the tendency of consumers to switch to lower or higher product or brand tiers conditional on changing economic conditions. Prominent examples for such switching behavior are consumers moving from national brands towards private labels (e.g., Lamey 2007) or from positional (status-conveying) goods and services towards non-positional ones (Kamakura and Du 2012) during economic contractions. Given, e.g., such "downgrading" during economic contractions, it may be possible that for some consumers the disconfirmation of expectations is positive ("I have downgraded and this lesser option is still meeting my needs"), whereas for some consumers the disconfirmation of expectations is negative ("I have downgraded and this lesser option is much worse than expected"). Since the books category is not an object of such downgrading biases, controlling for variations in a specific product (e.g., lower prices, less features, private labels etc.) is less of an issue. Thereby, the book category is also less prone to a related source of noise, namely a systematic and strategic release of new products that are customized to consumers' changed needs during economic downturns. Recessions are stressful and typically increase people's desire for simplicity and less choice (Flatters and Willmott 2009). Firms recognize these needs and try to cater to them, for instance, with cheaper products that exhibit less features and are easier to use. Such systematic changes of products on the market may influence how people evaluate these products. However, since books are less suited for being customized in such a way and the rather long production time of books makes it difficult to strategically time and release them, this bias is less of an issue.

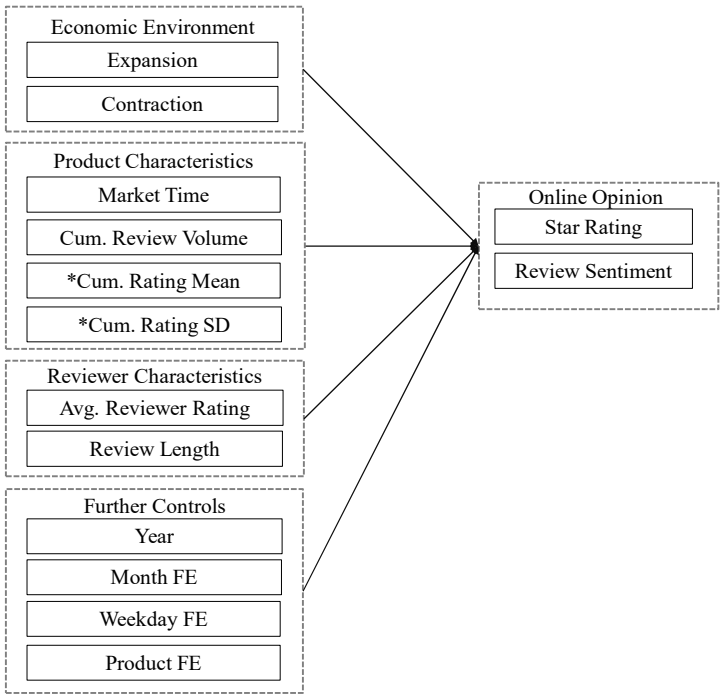
Finally, we employ quarterly US data on the gross domestic product (GDP) published by the US Bureau of Economic Analysis (BEA). Overall, we are thus able to build our analysis

on an encompassing data set of individual-level consumer rating and review behavior combined with aggregated economic measures.

4.2 Variable Operationalization

Our modeling approach considers three groups of factors influencing online opinion: (1) characteristics of the macroeconomic environment, (2) product characteristics, and (3) reviewer characteristics. Whereas the first group is derived from the literature on business cycles and is core to our research questions, the other two groups of factors are obtained from the literature on online opinion formation. Figure 1 provides an overview of all considered factors. Given the absence of similar studies in this regard, we provide two competing theoretical explanations on how business cycles may affect online opinion. We introduce both of them in the following sections.

Figure 1: Conceptual Framework



Note: Asterix (*) indicates variables being used in robustness check, FE, Fixed effects

Online opinion. Our models use two different measures representing consumers' online opinion about a product: the numeric rating (STARS) and the review sentiment (SENTIMENT) in online consumer reviews. STARS captures product ratings with the number of stars assigned by a reviewer to a given product (STARS ϵ {1, 2, 3, 4, 5}) and SENTIMENT measures the polarity in the sentiment extracted from the textual component of a product review. To calculate this variable, we perform a sentiment analysis based on an augmented dictionary lookup using R in version 3.5.1 (R Core Team 2018) and the package sentimentr in version 2.7.1 (Rinker 2019). The sentiment function is based on the dictionary provided by Jockers (2017) and accounts for potential valence shifters (i.e., negators, amplifiers, de-amplifiers, and adversative conjunctions) which are of particular relevance for stated satisfaction judgements.

Macroeconomic Environment. Our main explanatory variables capture the state of the macroeconomic environment, i.e., the business cycle, with two variables: the economic (1) EXPANSION and (2) CONTRACTION. To construct these measures, we first apply the Christiano-Fitzgerald (CF) random walk filter (Christiano and Fitzgerald 2003) to decompose the log-transformed quarterly GDP series into a trend and a cyclical component. The cyclical component constitutes the cyclical deviation from the long-term trend in the log-transformed GDP series. Then, we define the economic EXPANSION (CONTRACTION) as a period with an increase (decrease) in the cyclical component of the series. The magnitude of an economic EXPANSION (CONTRACTION) at any point in time is then defined as the difference between the concrete level of the cyclical component at time t and the prior trough (peak) in the cyclical component (Lamey et al. 2007; Van Heerde et al. 2013). We transform the series to a monthly sequence through linear interpolation to better match the level of aggregation in our ratings and review data (Van Heerde et al. 2013).

Product Characteristics. We also include variables to control for different and time-varying product characteristics in the respective online opinion platform. The variable

MARKETTIME captures the time a specific product has been available on the platform. Since we do not have the exact date a product has been added to Amazon's assortment, we approximate this information with the elapsed time in days between the focal review and the first review of a given product (Godes and Silva 2012). Furthermore, CUMULVOL measures the cumulative number of all reviews for a given product prior to the focal review (Godes and Silva 2012).[2] To demonstrate the robustness of our results, we account for further product characteristics that consider the ratings a specific product has previously received. Hence, CUMULMEAN and CUMULSD measure the cumulative mean and the cumulative standard deviation of all previous ratings for a given product prior to the focal review (Godes and Silva 2012).

Reviewer Characteristics. We also control for individual-level reviewer characteristics. Reviewers may be heterogeneous in how they assign concrete ratings to a product. Whereas some reviewers may be more positive in general and thus assign higher ratings, others may be more negative and assign lower ratings as a consequence. We control for this individual-level heterogeneity in general rating attitude of reviewers by constructing a reviewer-level average rating. Concretely, the variable REVAVG captures the average level of ratings assigned to all products reviewed by the reviewer other than the focal product (Godes and Silva 2012). Since only a fraction of these other products is in the core data set our estimation is based on, we exploit the size of the information available in the SNAP data set and construct this measure based on reviews from a certain reviewer across all available product categories. Furthermore, we control for the reviewer's motivation to submit a review by using a proxy for the costs of posting a review. When the costs of posting a review are high, only those reviews that are expected to have a significant impact on the prevailing average product rating would be submitted. Therefore, REVLEN measures the length of the textual component of a review by

[2] Godes and Silva (2012) name these variables TIME and ORDER instead of MARKETTIME and CUMULVOL to underline their interest in the dynamic effects these measures implicitly capture.

word count (Godes and Silva 2012). The necessary assumption, therefore, is that the reviewer knows ex ante about the review content and how much effort it may take to write it down. Longer reviews require more effort and are thus assumed to be more costly.

Further Controls. We further include a calendar year-level trend YEAR as it may interfere with the temporal time trend (Godes and Silva 2012). Finally, δ_p represents product fixed effects, δ_m the fixed effects of different months in a year to account for potential seasonal effects, and δ_d the fixed effects of different weekdays (Wang, Menon, and Ranaweera 2018).

Table 1: Descriptives and Correlation Matrix

		N	M	SD	Min	Max	1	2	3	4	5	6	7	8	9
1	STARS	148799	4.25	1.14	1.00	5.00									
2	SENTIMENT	148799	.19	.20	-1.89	1.44	**.44**								
3	EXPANSION	148799	.25	.58	.00	3.04	**-.06**	**-.08**							
4	CONTRACTION	148799	.72	.79	.00	4.69	**.03**	**.04**	**-.39**						
5	CUMULVOL	148799	1124.73	1499.95	1.00	6182.00	.00	**.03**	**-.12**	**.06**					
6	MARKETTIME	148799	240.27	552.96	1.00	5585.00	**-.02**	**-.02**	.00	**.01**	**.10**				
7	PERSAVG	130069	4.21	.73	1.00	5.00	**.36**	**.18**	**-.05**	**.02**	**-.01**	**-.03**			
8	REVLEN	145981	113.23	146.87	2.00	5251.00	**-.09**	**-.22**	**.14**	**-.07**	**-.11**	**-.05**	**-.07**		
9	CUMULMEAN	146548	4.29	.50	1.00	5.00	**.32**	**.20**	**-.07**	**.04**	**-.07**	**-.14**	**.13**	**-.06**	
10	CUMULSD	144849	.95	.41	.00	2.83	**-.25**	**-.15**	**.03**	**-.01**	**.20**	**.24**	**-.12**	**.01**	**-.81**

Notes: M = mean; SD = standard deviation; Min = minimum; Max = maximum.
Bold figures indicate significance at $p < .01$.

Table (1) provides descriptive statistics and correlations for key variables in our models. We standardize and mean-center all continuous variables before the estimation process. Additionally, Table (2) gives an overview of the distributions of our rating variable STARS across phases of economic EXPANSION and CONTRACTION and compares them with rating distributions in previous studies. As can be seen, the proportion of 5-star ratings during economic upturns is slightly lower than during downturns. Correspondingly, the proportion of lower star ratings is slightly higher during economic upturns than downturns. However, the general distribution of the star rating in our sample is comparable with previous studies.

Interestingly, around two-thirds of the ratings have been submitted in times of economic contractions which may be an indication of peoples' intensified reading activities when economic conditions get tough (Pfanner 2009).

Table 2: Distribution of Review Ratings

		Distribution (in %)			
RTG	**Total**	**Expansion**	**Contraction**	**Godes and Silva (2012)**	**Chevalier and Mayzlin (2006)**
5	60	58	61	59	53
4	21	21	21	16	20
3	9	10	9	8	11
2	5	5	4	6	8
1	5	6	5	11	9
N	148799	51090	97709	74750	256911

4.3 Empirical Model

To investigate the impact of business cycles on online opinion, we apply separate estimation procedures for our distinct online opinion variables STARS and SENTIMENT. Given the discrete and ordered nature of the STARS variable, we model the rating process with an ordered-logit model where U_{ip} is the reviewer i`s latent evaluation of product p (Godes and Silva 2012). Equation (1) defines the core model:

$$(1) \quad U_{ip} = \beta_1 EXPANSION_t + \beta_2 CONTRACTION_t + \beta_3 CUMULVOL_{ip} + \beta_4 MARKETTIME_{ip} + \beta_5 REVAVG_{ip} + \beta_6 REVLEN_{ip} + \beta_7 YEAR_{ip} + \delta_m + \delta_w + \delta_p + \varepsilon_{ip}$$

To account for the continuous nature of the SENTIMENT variable, we specify a linear regression model for reviewer i`s review of product p.[3] Equation (2) defines the core model:

[3] We visually inspect the distribution of SENTIMENT based on a density plot and find no evidence for a deviation from an approximately normal distribution.

$$(2) \quad SENTIMENT_{ip} = \alpha + \gamma_1 EXPANSION_t + \gamma_2 CONTRACTION_t + \gamma_3 CUMULVOL_{ip} + \gamma_4 MARKETTIME_{ip} + \gamma_5 REVAVG_{ip} + \gamma_6 REVLEN_{ip} + \gamma_7 YEAR_{ip} + \delta_m + \delta_w + \delta_p + \varepsilon_{ip}$$

To keep the empirical analysis computationally feasible, we randomly sample all reviews of 2,000 products which exhibit at least 20 evaluations (Wu and Huberman 2008).

4.4 Results

We use R (R Core Team 2018) in version 3.5.1 and the packages MASS (Venables and Ripley 2002) in version 2.0-1 for model estimation. Table 3 summarizes the results of our estimation process. Model (1) describes a base model without macroeconomic variables that we set up to verify the consistency of our findings with previous research. All our findings regarding effects of product characteristics, reviewer characteristics, and time controls are in line with previous research (Godes and Silva 2012, Wang et al. 2018). Thus, the parameter estimate of CUMULVOL (β_3 = -.0187, $p < .1$) indicates ratings to become more negative the more reviews are coming in for a specific product. The parameter estimate for MARKETTIME (β_4 = 1.9682, $p < .01$), however, indicates ratings to become higher the more time passes since a product's first review. Furthermore, we see the parameter estimate of REVAVG (β_5 = .7619, $p < .01$) to indicate a positive impact of reviewers' rating tendency. Thus, individual reviewers indeed have a certain propensity to give systematically higher ratings than do others. Moreover, the parameter estimate of REVLEN (β_6 = -.1281, $p < .01$) indicates that longer reviews, which are more costly to write, are associated with lower ratings. Finally, the parameter estimate of YEAR (β_7 = -1.6048, $p < .01$) indicates a negative time trend and thus ratings to become more negative over time.

Table 3: Business Cycle Effects on Online Opinon

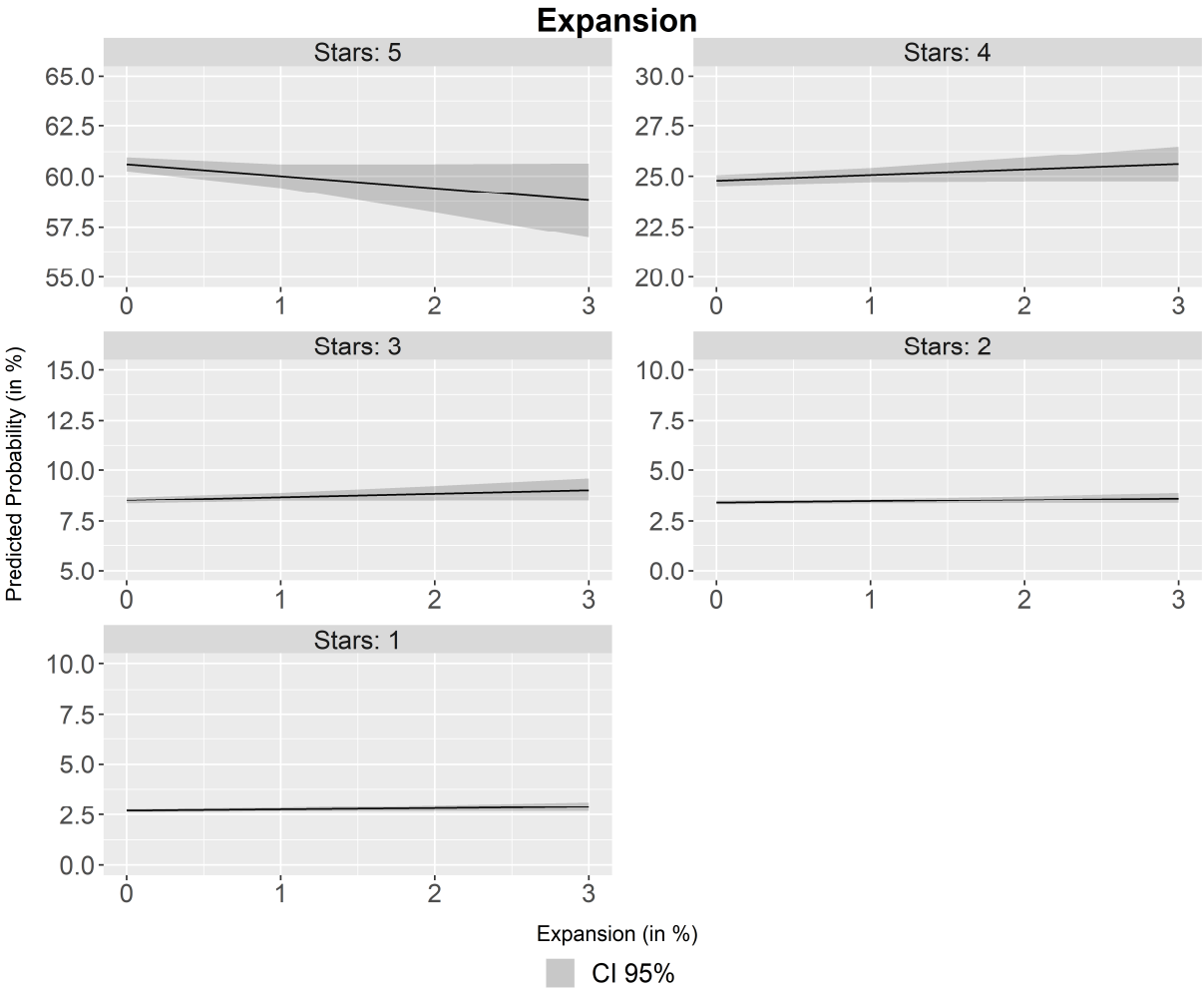
	Base Model	Business Cycle Effects		Business Cycle Effects	
		Main Models		Robustness Check	
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**
DV	**STARS**	**STARS**	**SENTIMENT**	**STARS**	**SENTIMENT**
IV					
EXPANSION		-.0143 *	-.0020 ***	-.0142 *	-.0021 ***
		(-.0080)	(.0007)	(.0082)	(.0007)
CONTRACTION		.0040	.0011 *	.0050	.0012 *
		(-.0072)	(.0006)	(-.0074)	(.0007)
CUMULVOL	-.0187 *	-.0185 *	.0038 ***	-.0184 *	.0035 ***
	(.0109)	(-.0109)	(.0009)	(.0110)	(.0010)
MARKETTIME	1.9682 ***	1.8628 ***	.0737	2.0471 ***	.0770
	(.0994)	(.0994)	(.0880)	(.1020)	(.0896)
REVAVG	.7619 ***	.7617 ***	.0271 ***	.7592 ***	.0272 ***
	(.0064)	(.0064)	(.0005)	(.0065)	(.0005)
REVLEN	-.1281 ***	-.1274 ***	-.0317 ***	-.1360 ***	-.0319 ***
	(.0059)	(.0059)	(.0005)	(.0061)	(.0006)
YEAR	-1.6048 ***	-1.5265 ***	-.0505	-1.6170 ***	-.0517
	(.0794)	(.0794)	(.0703)	(.0814)	(.0715)
CUMULMEAN				-.0345	.0051 ***
				(.0212)	(.0019)
CUMULSD				-.2186 ***	.0007
				(.0174)	(.0015)
Book effects	Fixed	Fixed	Fixed	Fixed	Fixed
Month effects	Fixed	Fixed	Fixed	Fixed	Fixed
Weekday effect	Fixed	Fixed	Fixed	Fixed	Fixed
N	127534	127534	127534	124406	124406
LL	-131729.7	-131727.0		-128900.2	
AIC	267509.3	267507.9	-70409.1	261858.4	-67639.8

Notes: Intercepts in the linear regressions and cut-off values in the ordered logistic regressions not shown, standard errors in parentheses.
DV = dependent variable; IV = independent variable; LL = log-likelihood; AIC = Akaike's information criterion.
*$p < .1$; **$p < .05$; ***$p < .01$.

Model (2) then includes our two macroeconomic variables and is the main ordered logit model for the impact of the business cycle on numerical online ratings. Here, the parameter estimate economic EXPANSION shows a negative and significant effect ($\beta_1 = -.0143$, $p < .1$) which indicates ratings to become lower when the economy expands. This finding is in line

with our expectation-disconfirmation explanation. Importantly, as we control for vertical quality with product-level fixed effects, this effect is independent of any specific product characteristics. The parameter estimate of economic CONTRACTION, in contrast, does not exhibit a significant effect ($\beta_2 = .0040$, $p \geq .1$). Thus, there is no indication for our expectation-disconfirmation explanation being true for economic contractions.

Figure 2: Effects of Economic Expansions on Numeric Ratings



To better understand the nature and magnitude of the negative impact of an economic EXPANSION on the different STAR-rating levels, we calculate predicted probabilities for each star-rating level over different values of the economic expansion. Figure 2 displays the corresponding effects. The negative effect on average, as indicated by β_1, is predominantly

driven by a decrease of the probability for a 5-star rating and an increase of the probability for a 4-star rating. Note that the mean product rating in the data sample is 4.25. Thus, each additional rating below a 5-star rating has a negative effect on this mean. The average probability for a 5-star rating when the macroeconomic performance does not deviate from its underlying growth trend, and thus per definition neither an economic expansion nor contraction occurs, is 60.6%. A 1% (2%, 3%) expansion in macroeconomic performance reduces the probability for a 5-star rating by -.6pp (-1.2pp, -1.8pp). Contrarily, the probability for a 4-star rating when does not deviate from its underlying growth trend is 24.8%. A 1% (2%, 3%) economic expansion then increases this probability by .3pp (.6pp, .8pp). The probabilities for 3-star, 2-star, and 1-star ratings also increase with an economic expansion, even though to a much smaller extent.

We repeat the model estimation with review SENTIMENT as our alternative dependent variable. Model (3) describes the results of the corresponding linear regression for the impact of the business cycle on review sentiment. In support of our previous finding, the parameter estimate of economic EXPANSION again shows a negative and significant effect ($\gamma_1 = -.0020$, $p < .01$), which indicates reviews to be written in a more negative way when the economy expands. Additionally, the parameter estimate of economic CONTRACTION shows a positive and significant effect ($\gamma_2 = .0011$, $p < .1$), indicating reviews to be written in a more positive way as the economy contracts. Both results are a strong support for our proposed expectation-disconfirmation explanation. Furthermore, the sentiment model confirms the importance of reviewer characteristics. While the parameter estimate for REVAG ($\gamma_5 = .0271$, $p < .01$) indicates that some reviewers in general write more positive reviews than others, the parameter estimate for REVLEN ($\gamma_6 = -.0317$, $p < .01$) associates longer and thus more costly reviews to be more negative in sentiment. In opposition to the rating model, the parameter estimate for

CUMULVOL in the sentiment model ($\gamma_3 = .0038$, $p < .01$) demonstrates an increase rather than a decrease in review sentiment as more reviews arrive for a specific product.

Similarly to previous research (Godes and Silva 2012, Wang et al. 2018), we demonstrate the robustness of our results by including further control variables in Model (4) and (5). These variables capture preceding opinions about a specific product.[4] Thus, we include a variable for the cumulative mean (CUMULMEAN) as well as a variable for the cumulative standard deviation of previous ratings (CUMULSD). In both models the effect of an economic EXPANSION remains robustly significant and negative. The economic CONTRACTION remains robustly significant and positive in the sentiment model.

5 The Moderating Role of Product Popularity

Our findings with regard to the direct effects of economic expansions and contractions on review sentiment and, in part, numeric ratings are in strong support of the proposed expectation-disconfirmation theory. Thus, economic contractions exhibit a positive impact on review sentiment while economic expansions show a negative effect on both numeric ratings and review sentiment. The question remains whether certain product characteristics are capable of attenuating or amplifying these impacts. From a marketer's perspective, an important characteristic is a product's popularity in the market, i.e., the number of evaluations it received. Popular products increase consumers' awareness of and reduce their uncertainty about a product, ultimately leading to increasing sales (Chen, Wang, and Xie 2011; Chintagunta, Gopinath, and Vekataraman 2010; Park, Gu, and Lee 2012). Yet the moderating role of product popularity on the business cycle-online opinion link needs further explanation.

[4] We have not included these control variables in the main analysis due to concerns about possible endogeneity issues (Godes and Silva 2012). Nevertheless, we see these model extensions as important demonstration of the robustness of our results.

For one, the availability of more information and consumer experiences about popular products should make it easier for potential buyers to verify whether their expectations may be met by a particular product. This reduces uncertainties about a purchase and should attenuate the existing negative disconfirmation effect during economic expansions. Correspondingly, a reduction of prepurchase uncertainties due to more available information should amplify the positive disconfirmation effect during economic contractions. However, as popular products also receive more attention in the marketplace, they also have a higher likelihood to raise potential buyers' awareness. With that, buyers might be influenced by the mere popularity of a product and the amount of information available rather than by the information content itself (Godes and Mayzlin 2009; Xiong and Bhadrawaj 2014). The underlying dynamic is well known as the bandwagon effect (e.g., Van den Bulte and Lilien 2001), in which people follow previous behavior to reduce perceived risks. However, when purchase decisions are based on the mere popularity of a product rather than the available information itself, it becomes more unlikely that expectations are met because the purchased products may not be a good fit. This should amplify the negative disconfirmation during economic expansions and attenuate an existing positive disconfirmation during contractions.

To further inspect the role of product popularity, we use the cumulative number of product reviews CUMULVOL as a proxy for product popularity (Vana and Lambrecht 2018). The number of received product reviews is a piece of information that is highly salient to the potential buyer prepurchase. It is displayed prominently on both individual product's webpages as well as product overview webpages. Thus, we expect potential buyers to consider this information both during purchase decision making as well in their satisfaction judgement after purchase. Moreover, increasing the number of product reviews and thereby implicitly the popularity of a product constitutes a pivotal objective of many word of mouth marketing campaigns. It therefore should be of great interest for any marketer to know whether driving

product review generation through marketing activities always leads to desired outcomes, i.e., positive opinions about a product, when business cycle impacts are considered.

Table 4: Moderation Effects of Product Popularity

	Product Popularity		Product Popularity	
	Main Models		Robustness Check	
	Model (6)	**Model (7)**	**Model (8)**	**Model (9)**
DV	**STARS**	**SENTIMENT**	**STARS**	**SENTIMENT**
IV				
EXPANSION	.0569 ***	-.0041 ***	-.0513 ***	-.0039 ***
	(.0100)	(.0009)	(.0101)	(.0009)
CONTRACTION	.0014	.0011 *	.0029	.0012 *
	(.0074)	(.0007)	(.0075)	(.0007)
CUMULVOL	-.0768 ***	.0011	-.0707 ***	.0010
	(.0137)	(.0012)	(.0137)	(.0012)
EXPANSION*CUMULVOL	-.1567 ***	-.0071 ***	-.1407 ***	-.0063 ***
	(.0225)	(.0021)	(.0227)	(.0021)
CONTRACTION*CUMULVOL	-.0073	.0004	-.0057	.0005
	(.0085)	(.0008)	(.0085)	(.0008)
MARKETTIME	1.8343 ***	.0711	2.0297 ***	.0749
	(.0995)	(.0880)	(.1021)	(.0896)
REVAVG	.7614 ***	.0271 ***	.7589 ***	.0272 ***
	(.0064)	(.0005)	(.0065)	(.0005)
REVLEN	-.1268 ***	-.0317 ***	-.1353 ***	-.0319 ***
	(.0059)	(.0005)	(.0061)	(.0006)
YEAR	-1.4966 ***	-.0481	-1.5973 ***	-.0497
	(.0795)	(.0703)	(.0815)	(.0715)
CUMULMEAN			-.0412 *	.0048 **
			(.0213)	(.0019)
CUMULSD			-.2190 ***	.0007
			(.0174)	(.0015)
Product effects	Fixed	Fixed	Fixed	Fixed
Month effects	Fixed	Fixed	Fixed	Fixed
Weekday effects	Fixed	Fixed	Fixed	Fixed
N	127585	127585	124426	124426
LL	-131700.9		-128879.4	
AIC	267459.9	-70420.8	261820.8	-67648.35

Notes: Intercepts in the linear regressions and cut-off values in the ordered logistic regressions not shown; standard errors in parentheses.
DV = dependent variable; IV = independent variable; LL = log-likelihood; AIC = Akaike's information criterion.
*$p < .1$; **$p < .05$; ***$p < .01$.

We re-estimate our main rating and sentiment models and include interaction terms of the macroeconomic variables and the proxy for product popularity. Table 4 summarizes the results of this additional estimation procedure. Model (2) shows the corresponding effects from the ordered logit model with STARS as the dependent variable. The parameter estimate of EXPANSION*CUMULVOL shows a significant and negative effect (β = -.1567, p < .01), indicating higher product popularity to further amplify existing negative effects of economic upswings on review ratings. We again calculate predicted probabilities for each star-rating level over different values of economic EXPANSION and CUMULVOL to gain further insights into the underlying interaction.

Figure 3: Moderating Effect of Product Popularity on Expansion-Rating Link

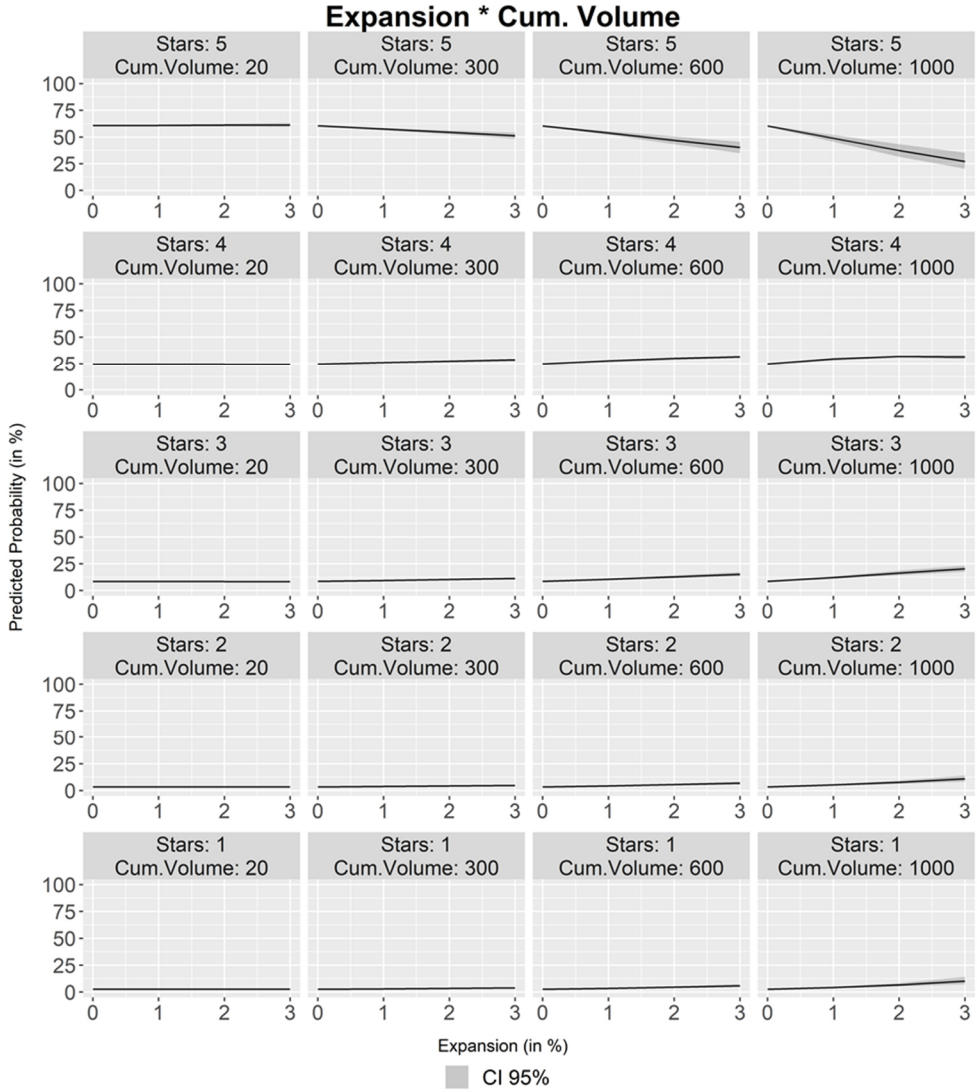
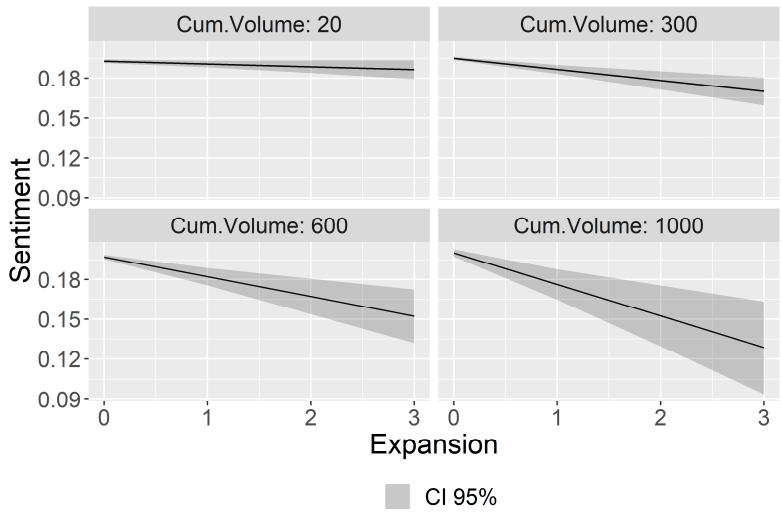


Figure 3 displays the corresponding effects at work, exhibiting a negative amplification through product popularity. Whereas for a less popular product with only 20 reviews the probability to receive another 5-star rating remains basically constant at a level of around 60% with increasing economic expansion, the impact on more popular products turns out to be much more severe. Products with over 1,000 reviews, for instance, show a reduction in the probability to receive another 5-star rating by -11.6pp (-23.0pp, -33.2pp) when the economy expands by 1% (2%, 3%). The probabilities for any other star rating lower than 5-stars at the same time increase by comparable magnitudes. These results are quite remarkable, especially since exhibiting hundreds or even thousands of reviews is not uncommon, particularly in the books category. The parameter estimate of CONTRACTION*CUMULMEAN, however, shows no significant interaction effect ($\beta = -.0073$, $p \geq .1$).

Figure 4: Moderating Effect of Product Popularity on Expansion-Sentiment Link



We rerun the model estimation with review SENTIMENT as our alternative dependent variable. Model (7) describes the results of the corresponding linear regression with added interaction terms. The parameter estimate of EXPANSION*CUMULVOL shows a negative and significant effect ($\gamma = -.0071$, $p < .01$). This confirms our previous finding with regard to

numeric ratings and indicates the negative impact of economic upswings on review sentiments to also amplify through product popularity. Figure 4 illustrates this interaction for different values of CUMULVOL. The parameter estimate of CONTRACTION*CUMULVOL, however, indicates no significant interaction effect (γ= .0004, $p \geq .1$).

In a final estimation step, we again demonstrate the robustness of our results by including the cumulative mean (CUMULMEAN) and the cumulative standard deviation of previous ratings (CUMULSD) as further control variables into the models. In both Model (8) and (9) the parameter estimates of the interaction EXPANSION*CUMULVOL remain robustly significant and negative.

6 Discussion

We discuss our findings according to the research questions stated at the beginning and clarify how answering these questions contributes to existing literature on business cycles in marketing and online opinion formation. In addition, we specify some important implications for marketers to offer concrete managerial action recommendations.

6.1 The Impact of Business Cycles on Online Opinion

Our results reveal that economic expansions and contractions have apparent and far reaching effects on the numeric ratings and review sentiment in online product reviews. The numeric ratings are, on average, negatively affected by economic expansions. This negative impact is particularly driven by a decline in the probability for a focal product to receive another 5-star rating. As such, an expansion by 1% (2%, 3%) in macroeconomic performance reduces the probability to receive another 5-star rating by -.6pp (-1.2pp, -1.8pp). Correspondingly, the probability for a focal product to receive another 4-star rating instead shows the strongest increase. Thus, an economic expansion by 1% (2%, 3%) increases the probability for another

4-star rating by .3pp (.6pp, .8pp). While the mean rating across all products and reviews in our data sample is 4.25, receiving a 4- instead of 5-star rating brings, on average, a devaluation of the product. The review sentiment in online product reviews, however, is affected by both economic expansions in a negative and contractions in a positive way. The viability of review sentiment as a measure of online opinion to capture both economic expansion as well as contraction effects may be based on its continuous and more fine-grained nature compared to the ordinal rating measure. Therefore, these results underline the importance to consider alternative measures of online opinion that are capable to capture possibly weaker signals and shifts in online opinions. Previous studies have predominantly relied on numerical ratings (e.g., Godes and Silva 2012; Moe and Trusov 2011; Wang, Menon, and Ranaweera 2018).

Overall, this is the first empirical study to show an existing link between economic expansions and contractions and numeric ratings and review sentiment. All those findings are in line with expectation-disconfirmation models (Anderson 1973) which suggest consumers to be less satisfied when the disparity between pre-purchase expectations and postpurchase performance increases and, correspondingly, more satisfied when their expectations are met.

6.2 The Moderating Role of Product Popularity

We extend our findings by considering CUMULVOL as a proxy for product popularity and argue for its capability to either attenuate or amplify existing business cycle effects. Popular products increase consumers' awareness of and reduce their uncertainty about a product, ultimately leading to increasing sales (Chen, Wang, and Xie 2011; Chintagunta, Gopinath, and Vekataraman 2010; Park; Gu, and Lee 2012). The popularity of a product is therefore likewise relevant for potential buyers and marketers. Moreover, to increase a products' popularity in the market oftentimes is a key objective in many word of mouth campaigns.

Our findings, however, indicate that product popularity may rather be a disadvantageous characteristic when being faced with changing economic conditions. As such, the negative impact of economic expansions on online opinion appears to be much more severe for popular products. For instance, for a less popular product with only twenty reviews the probability to receive another 5-star rating remains basically unaffected with increasing economic expansion. Products with over a thousand reviews, however, show a reduction in the probability to receive another 5-star rating by -11.6pp (-23.0pp, -33.2pp) when the economy expands by 1% (2%, 3%). This tendency also exist with regard to the review sentiment in online product reviews. However, product popularity has no significant effect on the relationship between economic downswings and review sentiment. Therefore, popular products loose with regard to their mean evaluation relative to less popular products during economic contractions, but do not exhibit appropriate gains in the subsequent economic contraction. Thus, popular products are in a more disadvantageous position when it comes to dealing with changing economic conditions compared to less popular products. However, it should be noted that these results are limited to the potential effects on consumers' online opinion and do not account for potential effects product popularity may have on sales performance.

By pursuing our research objectives, we contribute to existing literature on several forefronts. While the moderating role of business cycles on the consumer satisfaction-demand relationship has already drawn quite some attention (e.g., Fornell, Rust, and Dekimpe 2010; Yeung et al. 2013), a potentially preceding effect of changing macroeconomic conditions on satisfaction has been widely neglected. Moreover, research in this domain normally relies on survey-based satisfaction measures that are difficult and expensive to obtain on a large-scale individual level and over longer time periods. Therefore, Dekimpe and Deleersnyder (2017) recently have emphasized the importance of more research on the individual level and over longer time periods. We are broadening the existing research scope and base our analysis on

data containing individual online product reviews that are recognized to be a valid representation of consumers' satisfaction with a product (Moon et al. 2010; Mattwick and Mosteller 2017). This data is highly disaggregated, easily accessible, and available for nearly the past two decades, making it possible to capture the potential effects of multiple business cycles. Moreover, by relying on a continuous semi-dummy variable to identify the general state of the economy that captures not only different business cycle phases but also their concrete magnitude, we are able to generate richer insights about the underlying mechanisms during economic expansions and contractions.

Lastly, we also contribute to the literature stream on online opinion formation and follow a call by Godes and Silva (2012) to deepen insights on the antecedents of online opinion. We do so by demonstrating the macroeconomic environment to be an important driver of online ratings and review sentiment. Prior research in this domain has rather adopted a one-sided perspective on drivers within the opinion platform itself. Additionally, our results stress the importance of review sentiment as a measure of online opinion, which has been widely neglected in previous research. One reason may be the inconveniences unstructured text data brings along. However, the fine-grained and continuous nature of review sentiment compared to discrete rating scales has shown to be more extensively affected by economic expansions and contractions. Thus, review sentiment might be capable to capture weaker signals and therefore be a more precise indicator of consumer satisfaction.

6.3 Managerial Implications

Our results highlight how numeric ratings and review sentiment in online product reviews are in different ways affected by economic expansions and contraction. Although retailers and manufacturers, or publishers as for our focal product category, have little control

over the current state of the economy, knowing about likely changes in online opinion allows them to induce appropriate marketing actions.

As such, marketers should be particularly cautious when, e.g., considering online opinions in their marketing strategy decisions (Chen and Xie 2008; Cui, Lui, and Guo 2012) and reweigh them with regard to the current state of the economy. Particularly during economic expansions, more negative ratings and reviews may send false signals of product performance issues, which are not necessarily linked to unfavorable product attributes or bad quality. At the same time, more positive reviews during economic contractions may hide potential quality issues. Thus, marketers are well advised to carefully observe product performance beyond online opinion. In the light of a potential impact of online opinion on sales, marketers may consider targeted online word of mouth campaigns to support more positive ratings and reviews during economic expansions and thus to counteract negative trends. Contrarily, the increasing positive sentiment in reviews during economic contractions may be leveraged and reviews featured in other company-owned media outlets.

Importantly, the negative impact of economic expansions on numeric ratings and review sentiment appears to be much more severe for popular products. Therefore, marketers should be cautious when implementing word of mouth campaigns to increase product popularity and trigger product review generation. Depending on the current state of the economy, such actions may backfire rapidly and lead to a severe devaluation of a product on the opinion platform, ultimately leading to negative performance outcomes.

6.4 Limitations and Directions for Research

Our study is subject to some limitations that promise fruitful avenues for future research. One limitation relates to the selection of the book category as the focal context of research. We do so due to the category's size and covered time span in the data set as well as

its predominant presence in previous studies. More importantly, we rule out potential sources of noise that may arise due to consumers' switching towards lower or higher product and brand tiers as it is common in other product categories when economic conditions change (e.g., Lamey 2007). Future research, however, might consider categories of, e.g., rather utilitarian nature in which the influence of economic fluctuations may follow diverging mechanisms.

Second, although we show evidence for the impact of business cycles on online opinion which is in line with our proposed expectation-disconfirmation explanation, this argumentation is purely theoretical. To further strengthen this insight, it might be worthwhile to replicate the proposed effects in a controlled experiment to see whether the suggested underlying mechanisms, i.e., economic expansions (contractions) increase (decrease) consumer expectations which lead to changes in online opinion, actually hold true.

Third, considering potential particularities of books as our focal product category, it may be the case that economic expansions and contractions bring different segments of readers to the market. These may be readers with different tastes, otherwise reluctant readers who see books, e.g., as small luxuries and substitutes for goods they cannot justify in the face of budget constraints during tough economic times, or readers who intensively utilize reading as a means for escapism or self-improvement when the economy turns sour. These readers may also differ in terms of how they evaluate their purchases. Although we are able to control for some reviewer heterogeneity in our models, this control is far from perfect and requires a consideration of more specific reviewer characteristics.

Fourth, even though consumers' online opinion may be considered a direct measure of consumer satisfaction with a purchase, numeric ratings and review sentiment in online product ratings may be subject to some systematic biases. In particular, previous research has shown that self-selection biases exist such that predominantly buyers who are very satisfied or unsatisfied with their purchase expend the effort to submit a review (e.g., Godes and Silva 2012;

Li and Hitt 2008; Moe and Trusov 2011). Therefore, online opinions may exhibit rather extreme product evaluations that are not necessarily representative for the general population of consumers. This may limit the generalizability of our findings.

Fifth, we evaluate the state of the economy based on a filtering procedure of a quarterly GDP series. While this procedure is in line with previous research (e.g., Van Heerde et al. 2013), further indicators of the economic environment may be applicable. For instance, the University of Michigan's Index of Consumer Sentiment (e.g., Dhar and Weinberg 2016) may be an alternative which takes consumers' subjective evaluations of their finances and their expectations about the economic climate into account.

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Statutory Declaration

Eidesstattliche Erklärung

„Hiermit versichere ich an Eides Statt, dass die Arbeit ohne unerlaubte Hilfe angefertigt und keine anderen, als die angegebenen Quellen und Hilfsmittel benutzt wurden. Ich erkläre ferner, dass die den benutzten Werken wörtlich oder inhaltlich entnommenen Stellen als solche kenntlich gemacht wurden. Eine Überprüfung der Dissertation mit qualifizierter Software im Rahmen der Untersuchung von Plagiatsvorwürfen ist gestattet.“

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