THE EVOLVING BRAND-CONSUMER RELATIONSHIP – THE IMPACT OF BUSINESS CYCLES, DIGITAL PLATFORMS, AND NEW ADVERTISING TECHNOLOGIES

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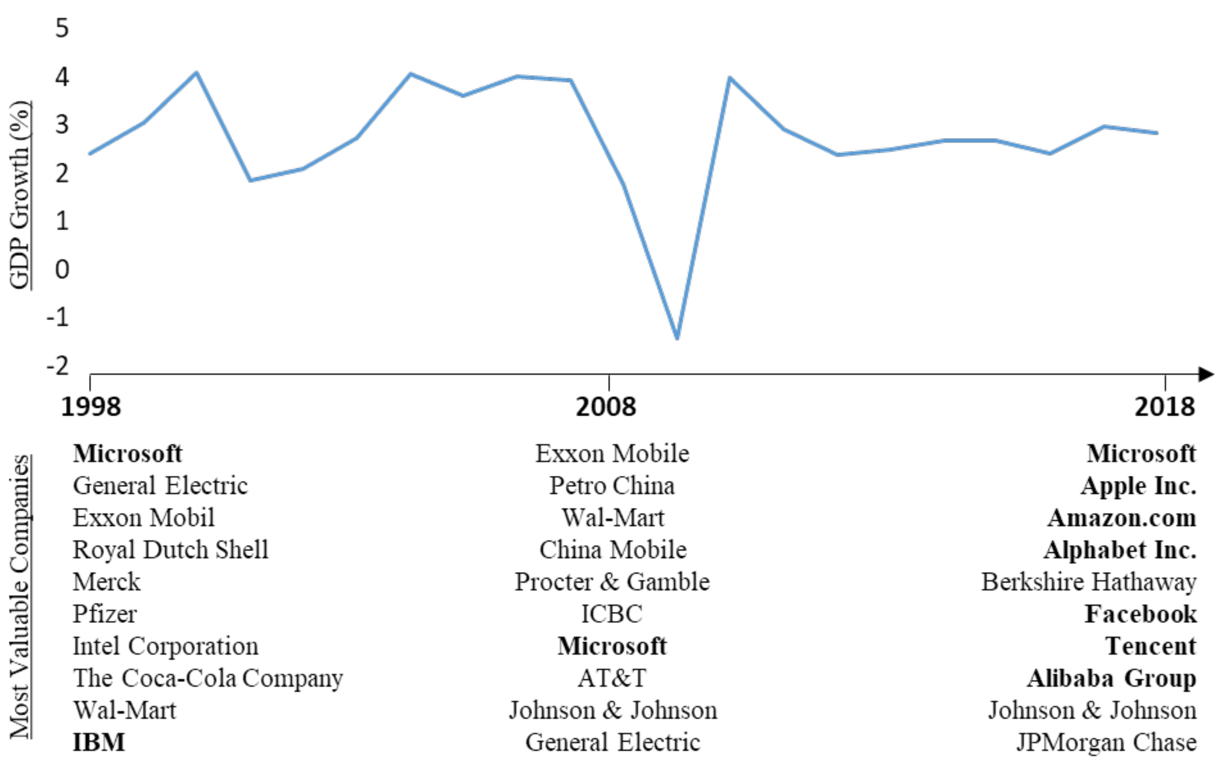
Synopsis

1 Introduction

The past two decades were marked by profound disruptions of consumers' daily lives and brands' established practices that have originated from two fundamental sources: intense economic turmoil and unprecedented technological progress. The unusually pronounced business cycle featured two major periods of severe recessions—the bursting of the dot-com bubble in the early 2000s and the global financial crisis followed by the European debt crisis from 2008 onwards— but also impressive expansions, with the current one experiencing a ten-year streak (NBER 2019). During the same time frame, tremendous technological progress has shaped virtually all areas of life and business. The extent of this development is easily demonstrated by comparing today's most valuable companies by market capitalization to those from ten or twenty years ago: In the year 2008, the top ten of the most valuable companies was dominated by petrol companies (Exxon Mobile and PetroChina), mobile carriers (e.g. AT&T) and consumer goods manufacturers (e.g. Procter & Gamble). By contrast, seven of today's top ten are technology firms, specifically Microsoft, Apple, Amazon.com, Alphabet Inc., Facebook, Alibaba Group, and Tencent (Financial Times 2019). Figure 1 illustrates these two major forces that have shaped the past two decades by means of worldwide GDP growth and the ten most valuable companies from 1998 to 2018. These disruptive times cause an evolution of the relationship between consumers and brands, creating opportunities to elevate existing connections and to build new ties but also putting established relationships to the test by introducing new competitors and changing consumer preferences.

Although business cycles are reoccurring events, they challenge companies and consumers each time (Dekimpe and Deleersnyder 2017). In recessions, many consumers have no other choice than to tighten their belt and reduce spending for example by postponing purchases (Dutt and Padmanabhan 2011) or switching brands and outlets (Ma et al. 2011). Even consumers that are not affected on a financial level often adjust their shopping habits, because their tastes, values, and willingness to purchase change as a reaction to macroeconomic conditions (Flatters and Willmott 2009; Kamakura and Du 2012; Katona 1979). Thus, consumers may abandon long-established relationships with brands in favor of cheaper alternatives. Prior research shows, that this may have lasting effects as consumers potentially stick with the alternatives even long after the recession is over (Lamey 2014; Lamey et al. 2007).

Figure 1: Illustration of the Past Decades' Economic and Technological Disruptions



Top: Annual worldwide GDP growth in % (Worldbank 2019).
Bottom: Top ten most valuable companies based on market capitalization (Financial Times 2019).

Two highly influential technological developments in this time frame from a marketing perspective have been digital platforms and digital advertising, dominating the academic discourse and constituting a crucial pillar for many of today's most successful companies: Each of the seven technology firms mentioned above has a business model that is based to a significant degree on digital platforms, online advertising, or both.

Digital platforms are orchestrators of connections between consumers, third parties, and devices (Boudreau 2017) that have disrupted numerous industries, such as AirBnb in the case of hoteling or Uber in ride hailing, by tapping into the consumer as a resource (Eckhardt et al. 2019; Parker, Van Alstyne, and Choudary 2016). Thus, the role of the consumer has changed drastically in the platform economy (Parker, Van Alstyne, and Choudary 2016), becoming a co-creator not only in her own value-creation process but also that of other consumers by providing platforms with data, reviews, ratings, content, and the like (Etgar 2008; Prahalad and Ramaswamy 2004; Trusov, Bucklin and Pauwels 2009). Additionally, the various parties and devices that are brought together on a platform create value and engage consumers beyond a purchase (Ramaswamy and Ozcan 2016, 2018). Take, for example, Under Armour's Connected Fitness platform: Consumers can track and optimize their workouts, share experiences with peers, and take part in challenges. Hence, the brand-consumer relationship becomes considerably more profound with a variety of different interactions and touchpoints throughout a day. Also, the traditional roles of consumers and brands evolve with consumers transitioning from value receivers to value providers and brands progressing from value providers to orchestrators of various value sources (Boudreau 2017; Kumar and Reinartz 2016).

Technological progress has also led to ever more sophisticated advertising technologies with various methods of targeting allowing brands to personalize their advertising and reduce wastage (e.g. Bleier and Eisenbeiss 2015; Goldfarb and Tucker 2011; Urban et al. 2013). Additionally, digital advertising has allowed small, financially more constrained brands to enter the advertising market because online, any size for an ad campaign can be accommodated irrespective of the advertising budget [1](Anderson 2006; Bergemann and Bonatti 2011). By contrast, traditional media channels have a fixed audience, defined by a magazine's number of

[1] In fact, I ran an ad on Facebook in order to recruite subjects for one of my experimental studies in this dissertation with a total ad budget of €15, yielding 3,420 impressions and 64 clicks.

readers or a TV channel's viewers, so that broadcasting a single 30-second TV ad can easily require five-digit budgets (Poggi 2018). Hence, digital advertising shapes the brand-consumer relationship by allowing virtually any company to craft targeted, personalized ads using highly engaging formats such as video ads (Anderson 2006; Bergemann and Bonatti 2011; Van Laer et al. 2014).

In three essays, my co-authors and I analyze how these two forces—the business cycle and the technological progress—affect the relationships between brands and consumers. I present an overview of the three essays and their submission-status in Table 1 and briefly describe each essay in the following before giving a more detailed summary in the next chapter.

Table 1: Overview of Dissertation Projects

Essay	Title	Author(s)	Status
I	Shifts Beneath the Surface: How Micro- and Macroeconomic Conditions Affect FMCG Shopping Strategies	Thomas P. Scholdra*, Julian R. K. Wichmann*, Maik Eisenbeiß, and Werner J. Reinartz	Under review (2nd round): *Journal of Marketing*
II	Transcending the Boundaries of Relationship Marketing: How Digital Platforms Create Value and Shape Consumers' Lifeworld and Habitus	Julian R. K. Wichmann, Nico Wiegand, and Werner J. Reinartz	Under review (1st round): *Journal of Marketing*
III	Skippable and Non-Skippable Ads—The Yin and Yang of Online Video Advertising	Julian R. K. Wichmann	Prepared for: *Journal of Marketing*

*The first two authors contributed equally to this work.
As (shared) first author in all three essays, I contributed significantly to the ideation, literature review, conceptualization, statistical analysis, and write-up of each essay.

The first essay, titled "*Shifts Beneath the Surface: How Micro- and Macroeconomic Conditions Affect FMCG Shopping Strategies*", in shared first authorship with Thomas Scholdra, and co-authored by Maik Eisenbeiß, and Werner Reinartz, empirically investigates how consumers' established relationships with brands and stores evolve over the business cycle. We use a household-panel data set from GfK Germany featuring daily FMCG purchases, which we enrich with publicly available macroeconomic data and brands' advertising spending from the Nielsen Company. Using a hidden Markov model specification, we allow for heterogeneity among consumers in terms of how they shop and react to changing conditions. We identify seven distinct shopping strategies that reveal consumers' preferences for brands (private-label versus national brand), stores (discounter versus supermarket), and price tiers (regular price versus price promotion). Our focal covariates, household income and changes in the business cycle, reflect microeconomic and macroeconomic conditions, respectively. Their coefficients reveal how consumers switch their shopping strategy as a result of changes in these conditions. Thus, we are able to pinpoint idiosyncratic coping strategies and their effect on consumer' brand-relationships. For example, we find that when conditions worsen, consumers with a preference for national brands are reluctant to abandon their established relationship and, instead, adopt strategies that allow them to continue purchasing brands but at a reduced price by capitalizing on price promotions or increasingly purchasing brands in discounters.

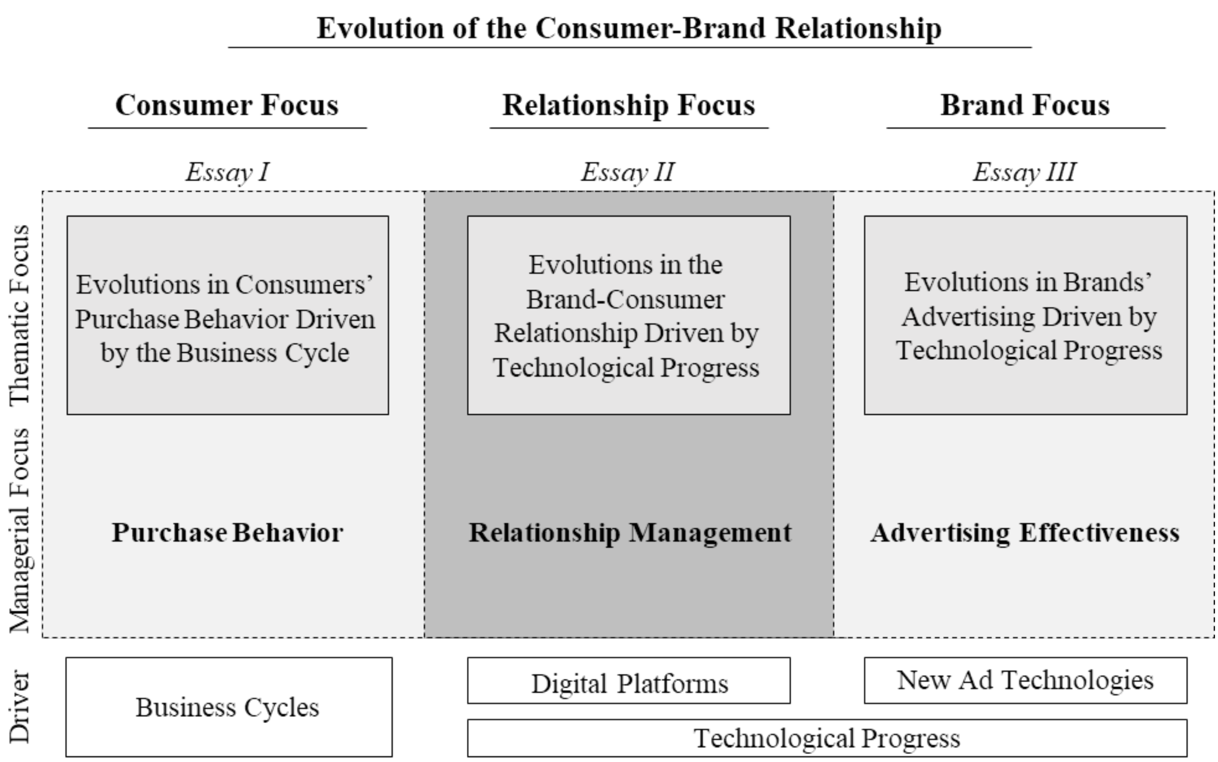
In the second essay, titled "*Transcending the Boundaries of Relationship Marketing: How Digital Platforms Create Value and Shape Consumers' Lifeworld and Habitus*", co-authored by Nico Wiegand and Werner Reinartz, we conceptually analyze how brands can use digital platforms to create superior consumer value that functions as a gateway into consumers' lifeworld and habitus. Specifically, we derive two dimensions of value that digital platforms are able to create for consumers, transactional value and relational value. For each, we define four value components and show how relational value components, in particular, are a powerful gateway for brands to intensify and extend their relationship with consumers across touchpoints and activities. Using new technologies and a platform architecture, brands can engage consumers in value-creating interactions on an ongoing basis, thereby, becoming part of their lifeworld and habitus. We argue that brands are thus in a position to exploit various "soft" and "hard" levers to shape consumers' behaviors and attitudes, for example in the form of gamification or behavioral engineering. Given this unprecedented influence that brands can exercise on consumers, we conclude with implications for marketers as well as governing institutions and consumers.

The third essay is single-authored and titled "*Skippable and Non-Skippable Ads – The Yin and Yang of Online Video Advertising*". In this experimental study, I analyze how consumers perceive skippable ads and how brands can use them most effectively. The results show that brands can deploy skippable alongside non-sippable ads to increase consumers' brand attitudes and, thus, sustain and intensify their consumer-relationships. Although the technology is almost ten years old (Pashkevich et al. 2012), research on the topic is scarce and uncertainty exists among advertisers whether to use skippable ads at all and how to use them most effectively. After all, advertisers are risking to miss out on ad exposures due to consumers' pronounced skipping behavior: 65-70% of ads are skipped, mostly even before the ten-second mark (Arantes, Figueiredo, and Almeida 2016; MAGNA 2017). Therefore, I shed light on this topic by means of three laboratory studies to derive how users perceive the ad format and how skipping an ad, thus disrupting the ad viewing experience, influences consumers' ad and brand perceptions. Additionally, I analyze the moderating effects of ads' narrative versus commercial focus as well as of combining skippable and non-skippable ad formats in subsequent ad exposures. Results reveal that consumers appreciate the increased level of control in skippable ads but the disruption that skipping causes to their ad viewing experience, even though self-imposed, depreciates their ad and brand perceptions. I demonstrate how brands can counteract this effect by providing a high commercial focus in skippable ads and also profit from complementing skippable ad exposures with initial forced full exposures.

The findings developed in this dissertation contribute to the academic discourse by rigorously analyzing how these developments influence consumers' purchase behaviors, attitudes towards brands, and the quality of their relationship. In doing so, this dissertation addresses two of the MSI research priorities 2018-2020 on cultivating the customer asset: "the customer-technology interface" and "macro trends influencing customer decision making" (Marketing Science Institute 2018). While the MSI and the academic literature to date is still talking about "customers", I primarily use the term "consumers" given the broad impact of the macroeconomic and technological evolutions that my co-authors and I research in the three essays. Additionally, as we specifically argue for in the second essay, brands are increasingly using technologies to build relationships, not just with their customers, but instead consumers in general, offering them substantial value irrespective of whether an actual purchase ever takes place.

For marketers, the essays present actionable implications that demonstrate how brands can weather these tumultuous times and use them to their advantage to build new relationships and intensify existing ones. A thematic overview of the three essays in relation to the dissertation topic is presented in Figure 2.

Figure 2: Classification of the Dissertation Projects



2 Summary of Dissertation Projects

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

Business cycles are a constant companion in consumers' daily lives: A US consumer born in 1980 has experienced five recession to this day (NBER 2019). Often they are inconspicuous but in times of pronounced recessions or expansions, they very saliently influence how and what we purchase (Dekimpe and Deleersnyder 2017; Ma et al. 2011). The most recent recession, the global financial crisis of 2008 was one of the most severe since the Great Depression (NBER 2019) and led to a reduction in annual spending by $4,000 for the average US household (The Economist 2011).

These savings are realized through different means: Consumers may postpone purchases (Deleersnyder et al. 2004; Dutt and Padmanabhan 2011) switch to cheaper brands and outlets (Dubé, Hitsch, and Rossi 2018; Lamey 2014; Lamey et al. 2007, 2012), and become more receptive to promotions (Cha, Chintagunta, and Dhar 2015; Ma et al. 2011). Hence, research shows that macroeconomic conditions such as recessions have considerable consequences for consumers' shopping behavior that challenge established brand-consumer relationships.

Especially in the FMCG context, consumers cannot simply postpone their purchases until conditions have improved and, therefore, are forced to switch to cheaper brands or to outlets that do not feature their preferred brands in order to cope with a more constrained budget. Once consumers have adopted and habituated new shopping behaviors, winning them back poses a challenge for brands (Dekimpe and Deleersnyder 2017; Lamey 2014; Lamey et al. 2007). Thus, business cycles can put a lasting strain on brand-consumer relationships.

While prior literature shows how the business cycle influences shopping behavior on an aggregate level (Dubé, Hitsch, and Rossi 2018; Lamey 2014; Lamey et al. 2007, 2012), literature on consumers' idiosyncratic adjustments is scarce. Hence, little is known about the different strategies that consumers employ to cope with changing conditions. For example, they may switch to cheaper brands, cheaper outlets, products on promotion, or any combination of these. Additionally, consumers' regular shopping behavior influences which strategy is suited to realize savings. For example, a consumer that usually shops premium brands in supermarkets has more options to reduce spending than a consumer usually purchasing private labels in discounters.

Given this gap in the literature, this essay uncovers the variety of consumers' reaction to the business cycle and its influence on their relationship with brands. We identify the different strategies that individual consumers and households apply to adjust their FMCG shopping to changes in macroeconomic conditions in the form of the business cycle and microeconomic conditions represented by household income. We employ a hidden Markov model (HMM) on a unique data set containing GfK Germany ConsumerScan panel data covering household-level daily purchases over a ten year period from 2004 to 2014, which we further enrich with macroeconomic data from the German Federal Statistical Office as well as brand-level advertising data from the Nielsen Company.

We identify seven distinct shopping strategies that consumers apply and uncover different switching patterns that are the result of changing micro- and macroeconomic conditions. For example, we find that even during adverse conditions, consumers value national brands and instead of switching to private labels tend to adjust by increasingly purchasing national brands on promotion or in discounters. Additionally, we find asymmetry in that all consumers tend to increasingly purchase national brands in supermarkets when their conditions improve, while the flip side of purchasing private labels in discounters during adverse conditions is less pronounced as some households remain reluctant to adopt this strategy.

Our contributions are threefold. First, we identify holistic shopping strategies by simultaneously observing which brands, in which stores, and in which price tier consumers purchase. Second, we reveal how consumers switch between these holistic shopping strategies due to micro- and macroeconomic changes. Third, we show that individual households not only experience the severity of economic changes differently, they also adjust to changing conditions in different ways.

For the brand-consumer relationship, we reveal that while recessions are a real stress test for established relationships, consumers are still reluctant to give up their preferred brands. Brands should invest countercyclically in marketing activities such as price promotions (Deleersnyder et al. 2009; Lamey et al. 2007, 2012) and adopt new outlets such as discounters in order to sustain their consumer-relationships.

2.2 Essay II: Transcending the Boundaries of Relationship Marketing: How Digital Platforms Create Value and Shape Consumers' Lifeworld and Habitus

The technological advances of the past years have led to an ever-closer integration of smart, connected devices into consumers' daily lives. Almost every aspect of their day-to-day activities – from their workout to their commute, nutritional intake, sleeping patterns, and vital signs – can be recorded, tracked, and transmitted. Thus, these devices are an interface to the consumer, and brands are competing for dominance over it (Reinartz, Wigand, and Imschloss 2019). Digital platforms are a potent tool that allows brands to access and leverage this interface. Whereas traditionally digital platforms were exchange-focused such as matchmaking platforms (Wu, Zhang, and Padmanabhan 2018), marketplaces (Rysman 2009), and lateral exchange markets (Perren and Kozinets 2018), today's platforms are highly relationship-focused. They orchestrate a variety of activities, parties, and devices (Boudreau 2017) that together create superior value for consumers by perpetually engaging consumers in value-creating interactions (Ramaswamy and Ozcan 2018).

In this essay, we analyze and conceptualize this novel type of value creation and show how it allows brands to form ongoing relationships with consumers, blending and ultimately shaping their lifeworld and habitus.

We first define and differentiate the various platform terminologies that are used in academia and business. We classify these various platform types along two dimensions – transactional and relational value creation – and derive four distinct value components for each dimension. We show that each of these components has been considerably elevated through technological advances such as automated recommender systems (Lee, Kim and Rhee 2001) and content curation mechanisms (Lazer 2015), self-quantification (Kelly 2016; Wolf 2010), and user-generated content (Kohler et al 2011; Trusov, Bucklin and Pauwels 2009).

While most platforms in the market still have a strong transactional focus, we argue that platforms that create relational value—which we call relational digital platforms or RDPs—present novel opportunities for brands because their value creation addresses consumers' higher-level goals (Belk 1988; Pieters, Baumgartner, and Allen 1995). For example, a platform like Under Armour's Connected Fitness helps consumers to achieve abstract, high-level goals such as living a fit and healthy life by creating value along all four relational value components that we identify: customization value, self-actualization value, social value, and hedonic value. So while transactional platforms only lead to individual interactions that relate to the specific purchase or exchange occasion (Ramaswamy and Ozcan 2018), RDPs are used by consumers on an ongoing basis along their pursuit of these higher-level goals long before, after, and even independent of an actual purchase. As a consequence, the brand-consumer relationship becomes more profound than ever before as each value-creating interaction makes the brand increasingly indispensable to consumers (Hoffman and Novak 2018).

Drawing from sociology, we show that this development allows brands to use RDPs and their value creation as a gateway into consumers' lifeworld and habitus, entering their "total sphere of experiences […] in the pursuit of the pragmatic objectives of living" (Schutz 1970, p. 320). Once in this position, an RDP can even shape consumers' lifeworld and habitus as it sits at the nexus of the interactions and orchestrates the information that is transmitted to the consumer. We show that this "colonization" of consumers' lifeworlds (Habermas 1987) becomes even more powerful through various "soft" and "hard" levers that brands can employ on the platform in terms of gamification, nudging, behavioral engineering, and governance structures.

We conclude this essay by raising awareness for possible adverse outcomes for brands, consumers, and society such as discrimination and manipulation, and present appropriate management and policy recommendations. We especially advocate that brands should not realize everything that is technically possible but build a team of marketers, psychologists, sociologists, and behavioral scientists that assesses whether platform features are ethically and socially acceptable and ensures that RDPs build mutually beneficial relationships between brands and consumers.

2.3 Essay III: Skippable and Non-Skippable Ads – The Yin and Yang of Online Video Advertising

Traditional linear TV is a mass medium that quite literally *broad*casts identical content and ads to millions of viewers. This severely limits the possibilities for brands to individualize consumers' ad experiences. However, as video content consumption is increasingly moving towards internet-connected devices, for example in the form of smart, connected TVs, online streaming services, and video platforms, new advertising technologies evolve that break up past rigidities and open up new opportunities for brands.

One of these technologies comes in the form of skippable ads, a new advertising format introduced by YouTube in 2010 (Pashkevich et al. 2012) and since then being widely adopted with 80% of marketing managers reporting they use skippable ads to some degree (IAB Europe

2018). Skippable ads allow consumers to skip the ad by clicking a button but only after they have watched it for a minimum required amount of time, usually five seconds (Campbell et al. 2017). Thus, they differ substantially from traditional video ads because the advertising brand exposes consumers to at least a fraction of the ad while also explicitly granting the option to avoid the ad. Skipping an ad, therefore, represent a unique form of advertising avoidance because it neither eliminates the ad in its entirety as usually the case with zapping or using ad-blocking software (Campbell et al. 2017; Dukes, Liu, and Shuai 2019) nor distorts it as is the case with zipping (i.e. fast-forwarding through prerecorded content; Stout and Burda 1989).

To date, research on this ad format is scarce and has primarily analyzed the antecedents of skipping (e.g. Belanche, Flavián, and Pérez-Rueda 2017a, 2017b; Campbell et al. 2017; Jeon et al. 2019). However, no research to date has examined in detail how consumers perceive brands and their ads when they are exposed to a skippable vis-à-vis regular, non-skippable ad and how the act of skipping influences their ad and brand perceptions. In this essay, I address this gap and identify how and why skippable ads can improve but also mitigate consumers' ad and brand perceptions. Additionally, I present opportunities for brands to optimize the effectiveness of skippable ads and, thus, to intensify their relationships with consumers through higher brand awareness and more favorable brand attitude.

Using three experimental studies that replicate typical online video viewing experiences, I show that skippable ads are able to reduce consumer irritation by elevating perceived control and decreasing perceived intrusiveness. At the same time, however, they also reduce consumers' enjoyment of the ad creative as a consequence of the large degree of habitually driven skipping. Supported by transportation theory (Green and Brock 2000; Van Laer et al. 2014), the results suggest that skipping undermines the persuasive power of ads with a narrative focus (Escalas 2004a, 2004b) and leads to irritation because it disrupts consumers' ad experience. Additionally, I find that the increased level of perceived control in skippable ads can also cause irritation by increasing cognitive load. My results demonstrate that brands need to employ distinct strategies for skippable versus non-skippable ads because consumers show better ad and brand perceptions for skippable ads that use a brand-focused creative whereas non-skippable ads perform better with a narrative focus. Finally, it becomes evident that skippable and non-skippable ads should not be regarded as substitutes as currently is the case across academia and business (e.g. Pashkevich et al. 2012; Campbell et al. 2017; Dukes, Liu, and Shuai 2019). Instead, I find that they complement each other's strengths and weaknesses, and, accordingly, brands should use skippable alongside non-skippable ads to evoke optimal brand perceptions.

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ESSAY I: 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, shopping strategies, income shocks, FMCG market

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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:

1) Identify and characterize distinct shopping strategies based on households' brand type, store format, and price tier preferences.
2) 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.
3) 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 Conceptual Background

2.1 Related Literature

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 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 and colleagues (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.

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.

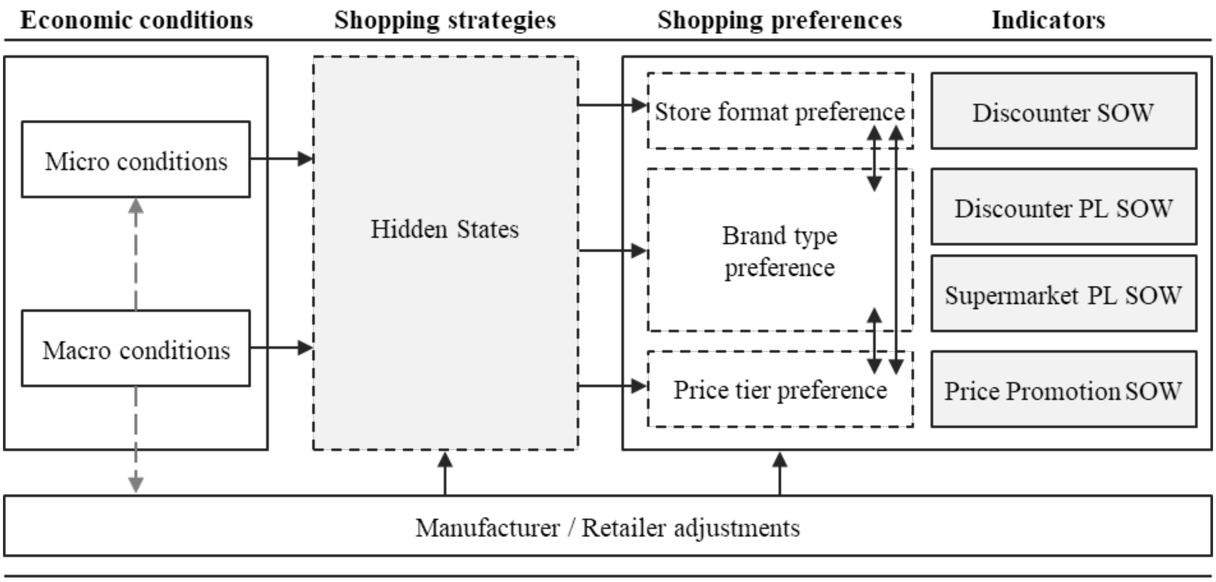
Table 1: Literature Overview and Contribution

Authors	**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	✓	✓	✓	✓

2.2 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, 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. 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 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)

3 Data

3.1 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. 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..

3.2 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 variation 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 Web Appendix A.

3.3 Variable Operationalization

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).

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

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. 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 (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).

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 and colleagues (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. Table 2 contains an overview of all variables; Web Appendix B offers details regarding the construction of the marketing mix variables. In addition, Table 3 provides the correlations for all specified variables.

Tabel 3: Descriptice Statistics 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.

4 Model

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.

4.1 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:

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

where

$$(2) \qquad \begin{aligned}\mathrm{SocioDem}_{ht0}=&\beta_{s_{t0}}^{1,\mathrm{SocioDem}}\mathrm{Income}_{ht0}+\beta_{s_{t0}}^{2,\mathrm{SocioDem}}\mathrm{HHSize}_{ht0}\\&+\beta_{s_{t0}}^{3,\mathrm{SocioDem}}\mathrm{Age}_{ht0}+\beta_{s_{t0}}^{4,\mathrm{SocioDem}}\mathrm{Kids}_{ht0},\end{aligned}$$

such that $\alpha_{s_{t0}}$ is the fixed intercept for the initial state s_{t0}; $\lambda_{hs_{to}}$ 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; $\mathrm{SocioDem}_{ht0}^{r}$ includes household-specific sociodemographic variables (r = 1, … , R) for the initialization period t0; and $\beta^{r}_{s_{t0}}$ captures the effects of the r-th variable on the probability of being in initial state s_{t0}.

4.2 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

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

with

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

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

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

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.

4.3 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:

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

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

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

(10) $$\text{PromoSOW}_{\text{ht}} = \alpha_{s_t}^{\text{Promo}} + \beta_{s_t}^{1,\text{Promo}} \text{PricePromo}_{\text{ht}} + \gamma_{s_t}^{\text{Promo}} \text{PromoSOW}_{\text{ht-1}} + \delta^{\text{Promo}} \text{Quarter}_t + \varepsilon_t^{\text{Promo}},$$

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 ($\text{DiscSOW}_{\text{ht-1}}$, $\text{PLDiscSOW}_{\text{ht-1}}$, $\text{PLSupSOW}_{\text{ht-1}}$, $\text{PromoSOW}_{\text{ht-1}}$), 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 ($\text{PriceDisc}_{\text{ht}}$, $\text{PricePLDisc}_{\text{ht}}$, $\text{PricePLSup}_{\text{ht}}$, $\text{AssrtDisc}_{\text{ht}}$, $\text{AssrtPLDisc}_{\text{ht}}$, $\text{PricePromo}_{\text{ht}}$, $\text{AdvDisc}_{\text{ht}}$, 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.

5 Results

5.1 Model Estimation and Selectin

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 5000 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 1000 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, CAIC.

5.2 Identified Shopping Strategies Based on Household Shopping Preferences

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.

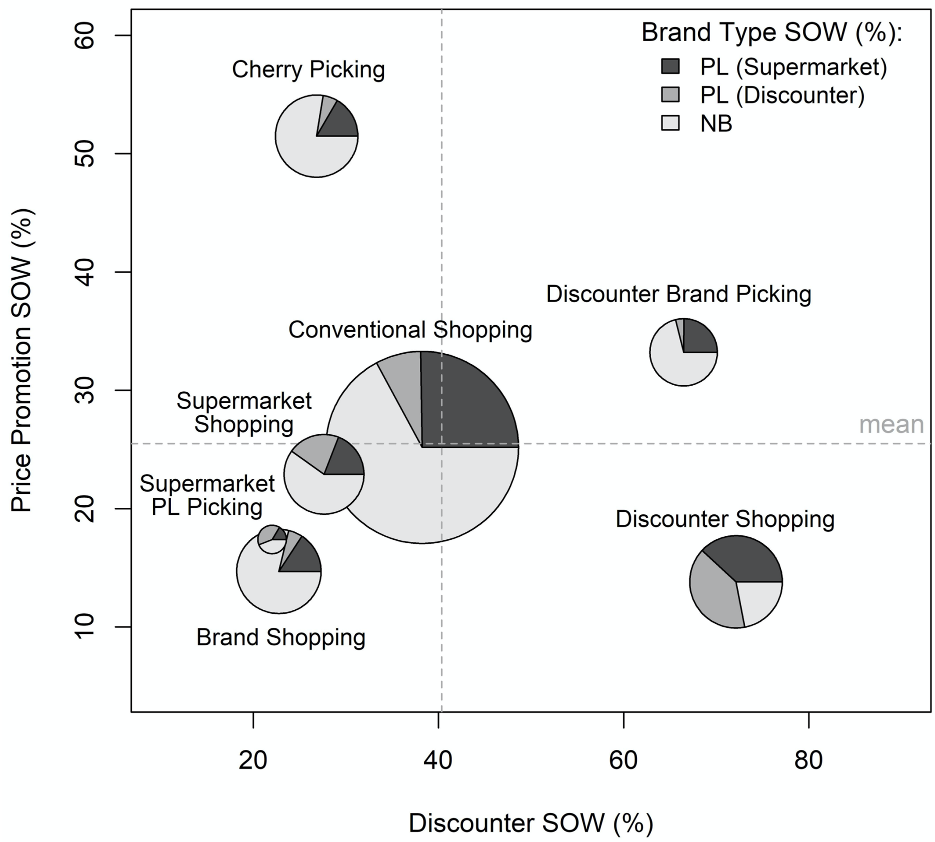
Second, some distinctive differences mark the strategies with regard to their underlying shopping preferences, as displayed in Figure 2. Compared with the sample averages (DiscSOW 40.3%, PLDiscSOW 27.7%, PLSupSOW 8.1%, PromoSOW 25.5%), households that pursue Strategy 4 show similar shopping preferences 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%), 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 Profils

	Shopping Strategy							
Panel A	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Overall**
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	127.04
Value (€)	115.5	131.4	139.4	199.3	132.7	77.2	165.6	137.32
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	

Table C1 in Web Appendix C provides estimation results for the initial assignment of shopping strategies to households on the basis of their sociodemographic characteristics. 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



5.3 Household Strategy Switching Due to Changing Micro- and Macroeconomic Conditions

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 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 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	**27.2**	11.56	11.71	8.11	20.32	13.66	10.09
2	7.51	**10.38**	15.18	7.1	7.43	11.39	14.24
3	10.48	24.03	**9.72**	4.85	20.67	23.5	15.75
4	36.22	32.36	36.28	**70.83**	21.37	24.26	25.67
5	9.68	5.68	10.85	3.5	**7.98**	9.65	12.83
6	1.25	1.15	2.46	0.43	2.43	**2.69**	2.46
7	7.66	14.82	13.8	5.17	19.8	14.85	**18.96**

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: Micro- and Macroeconomic Conditions and Impact on Strategy Changes

Strategy in t – 1	Strategy in t	Variable	Coef.	SE	Z-value		Wald(0)		DF
		Income					135.342	***	42
1	**3**	**Income**	0.301	0.112	2.699	***			
3	**5**	**Income**	-0.843	0.339	-2.491	**			
3	**6**	**Income**	-1.363	0.380	-3.584	***			
3	**7**	**Income**	-0.667	0.354	-1.886	*			
4	**1**	**Income**	-0.198	0.074	-2.667	***			
4	**2**	**Income**	-0.259	0.056	-4.626	***			
4	**3**	**Income**	0.175	0.106	1.650	*			
4	**5**	**Income**	-0.303	0.080	-3.793	***			
4	**6**	**Income**	-0.391	0.216	-1.805	*			
7	**6**	**Income**	-0.458	0.237	-1.931	*			
		Expansion					80.146	***	42
1	**5**	**Expansion**	0.253	0.137	1.851	*			
1	**7**	**Expansion**	0.331	0.181	1.827	*			
2	**1**	**Expansion**	-0.366	0.171	-2.148	**			
2	**5**	**Expansion**	-0.334	0.194	-1.723	*			
2	**6**	**Expansion**	-0.807	0.373	-2.163	**			
3	**1**	**Expansion**	-0.679	0.259	-2.619	***			
3	**4**	**Expansion**	-0.489	0.262	-1.868	*			
3	**7**	**Expansion**	-0.723	0.271	-2.671	***			
		Contraction					49.106		42
1	**5**	**Contraction**	0.223	0.119	1.877	*			
4	**7**	**Contraction**	0.223	0.109	2.052	**			
5	**7**	**Contraction**	0.357	0.187	1.908	*			

***$p < .01$; **$p < .05$; *$p < .1$.

Notes: 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: Shopping Strategy Transitions Due to Income Loss and Marketplace 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 (Table 9). 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.

Table 9: Shopping Strategy Transitions Due to Expansions and Marketplace 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

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 (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: Shopping Strategy Transitions Due to Contractions and Marketplace Consequences

			Consequences for:		
Switches from	**Focal Strategy**	**Switches to**	**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		+ / –	+	–

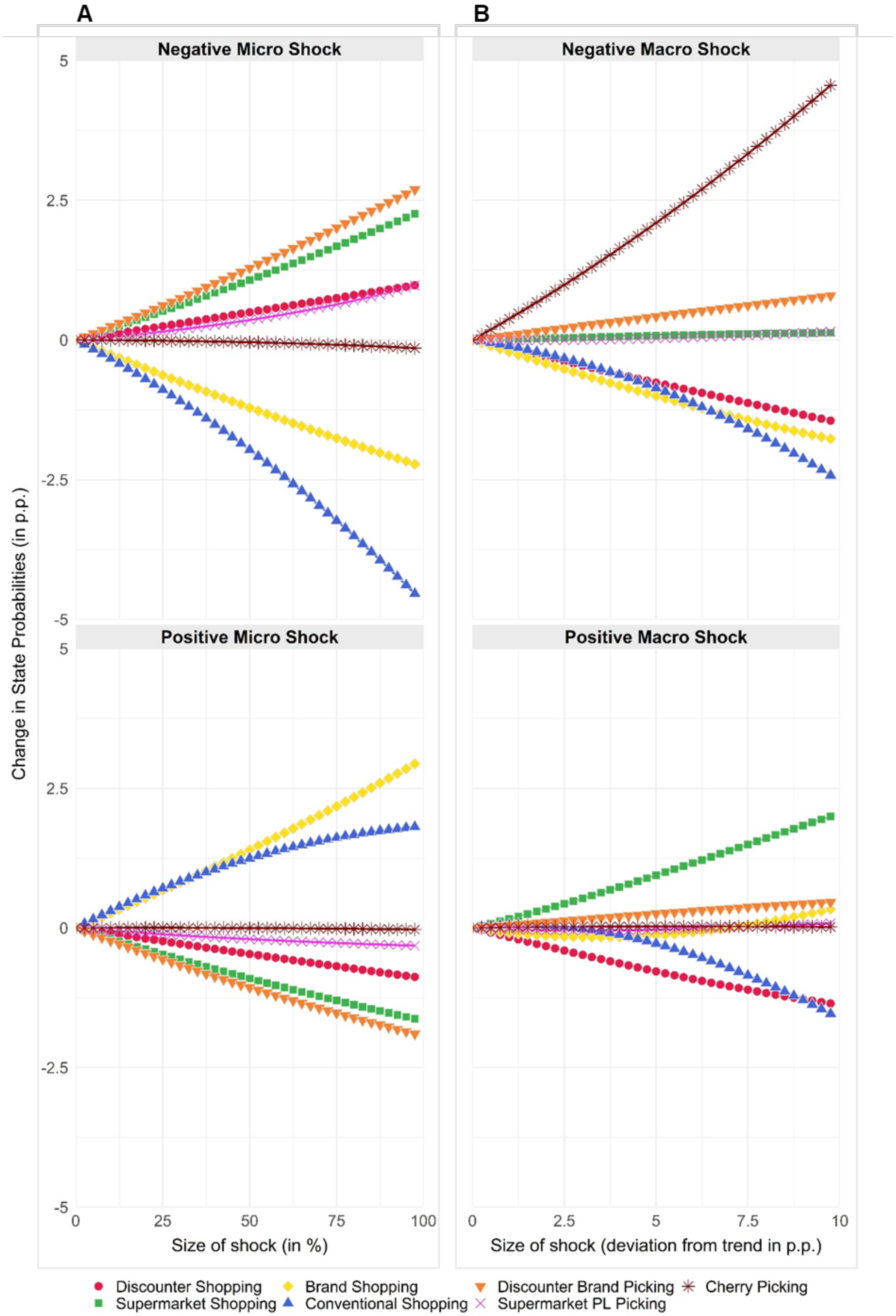
Notes: ↗ increased probability to switch, ↘ decreased probability to switch
[a]based on transition matrix

5.4 Sensitivity of Shopping Strategies to Changes in Micro- and Macroeconomic Conditions

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 2.5 percentage point increments; for a positive (negative) macroeconomic shock, we gradually increase the mean economic expansion (contraction) in .25 percentage point increments.

Figure 3 provides an overview of the simulation results. 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 -1.97 percentage points, while an equivalent income gain increases the probability of this strategy only by +1.25 percentage points. 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.

Figure 3: Effects of Micro- and Macroeconomic Conditions on Shopping Strategy Probabilities



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 5 percentage points decreases the probability of a Discounter Shopping strategy by -.62 percentage points, and an equivalent economic contraction decreases it by -.77 percentage points. A similar pattern, with varying magnitudes across economic expansions and contractions, occurs for the less price sensitive Conventional Shopping strategy, such that a 5 percentage point economic contraction (expansion) decreases the probability of this strategy by -.63 (-.27) percentage points. Shocks in economic contraction and expansion also both increase the probability that households adopt a Discounter Brand Picking strategy, by +.34 and +.25 percentage points, respectively. Then other shopping strategies are sensitive only to either economic expansions or contractions. For example, a 5 percentage point economic contraction shock increases the probability of pursuing a Cherry Picking strategy by +1.66 percentage points, but an economic expansion has no effect.

The Supermarket Shopping strategy instead is sensitive to economic expansions (+.93 percentage points) but not 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.

6 Discussion

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.

6.1 Shopping Strategies Based on Households' Shopping Preferences

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).

6.2 Switching Strategies in Response to Changing Conditions

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.

6.3 Sensitivity of Shopping Strategies to Changes in Conditions

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 Implication

7.1 Managerial Implications

Our results reveal the existence of various shopping strategies and highlight how households switch strategies due to changing micro- and macroeconomic conditions. While manufacturers and retailers have little control over these events, knowing the associated reactions of their customer base allows them to optimize their marketing mix preemptively. In addition, managers can tailor their marketing mix 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.

7.2 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 in different product categories, such as utilitarian versus hedonic goods, may provide further insights. In doing so, researchers might identify product categories that are particularly susceptible or resistant to changes in consumers' shopping strategies.

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APPENDIX ESSAY I

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	0.7	2.9	5.00
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 €	0.7	0.9	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	0.2	0.4	0.6
5+ children	0.0	0.1	0.2

* 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: Marketing Mix Variables

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:

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

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:

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

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:

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

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:

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

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:

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

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 ($\sum_{k=1}^{K} \text{AssrtSize}_{kht}\, bs_{kht0}$), 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:

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

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 calculated as:

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

where $\text{PriceTier}_{\text{lht}}$ 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 ($\sum_{l=1}^{L} \text{PriceTier}_{\text{lht}} \text{ts}_{\text{lht0}}$), 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 $\text{PriceTier}_{\text{lht}}$ is calculated as:

$$\text{PriceTier}_{\text{lht}} = \sum_{c=1}^{C} \text{PriceTier}_{\text{lct}} \, \text{cs}_{\text{hct0}},$$

where $\text{PriceTier}_{\text{lct}}$ 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 $\text{PricePromo}_{\text{ht}}$ 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:

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

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 ($\sum_{j=1}^{J} \text{Adv}_{\text{jt}}$), 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 $\text{AdvDisc}_{\text{ht}}$ 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:

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

where Adv_{kht} is the advertising spending, cumulative over brand type k at time t relative to the average advertising spending across brand types ($\sum_{\text{k=1}}^{\text{K}}\text{Adv}_{\text{kt}}$), 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	0.268	0.179	1.494		486.054	***	6
2	Intercept	0.190	0.175	1.085				
3	Intercept	0.300	0.279	1.074				
4	Intercept	2.375	0.127	18.759	***			
5	Intercept	-0.462	0.230	-2.007	**			
6	Intercept	-2.247	0.524	-4.289	***			
7	Intercept	-0.423	0.275	-1.536				
1	Income	-0.023	0.149	-0.152		8.909		6
2	Income	-0.011	0.165	-0.064				
3	Income	0.052	0.179	0.290				
4	Income	0.165	0.105	1.571				
5	Income	-0.517	0.211	-2.447	**			
6	Income	0.155	0.351	0.442				
7	Income	0.179	0.185	0.966				
1	HHSize	0.084	0.238	0.355		12.985	**	6
2	HHSize	0.155	0.252	0.614				
3	HHSize	0.035	0.273	0.127				
4	HHSize	0.609	0.177	3.443	***			
5	HHSize	0.046	0.301	0.153				
6	HHSize	-1.252	0.738	-1.697	*			
7	HHSize	0.323	0.281	1.148				
1	Kids	0.071	0.240	0.296		6.470		6
2	Kids	-0.172	0.262	-0.656				
3	Kids	-0.845	0.517	-1.634				
4	Kids	-0.126	0.180	-0.697				
5	Kids	-0.283	0.380	-0.745				
6	Kids	1.220	0.653	1.868	*			
7	Kids	0.135	0.282	0.479				
1	Age	-0.037	0.142	-0.262		7.708		6
2	Age	-0.091	0.154	-0.593				
3	Age	-0.360	0.169	-2.132	**			
4	Age	0.169	0.106	1.599				
5	Age	-0.019	0.157	-0.120				
6	Age	0.130	0.314	0.415				
7	Age	0.208	0.190	1.094				
1	Factor	0.759	0.154	4.930	***	54.215	***	6
2	Factor	0.065	0.183	0.354				
3	Factor	0.142	0.193	0.735				
4	Factor	0.106	0.119	0.887				
5	Factor	0.023	0.205	0.113				
6	Factor	0.377	0.380	0.994				
7	Factor	-1.472	0.234	-6.284	***			

***$p < .01$; **$p < .05$; *$p < .1$.

Notes: 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	0.155	253.000	***	64009.098	***	1			
	State 1	24.096	0.305	78.893	***	14958.757	***	6			
	State 2	-7.988	0.329	-24.274	***						
	State 3	-12.967	0.330	-39.268	***						
	State 4	0.714	0.170	4.198	***						
	State 5	22.666	0.312	72.566	***						
	State 6	-15.938	0.638	-24.970	***						
	State 7	-10.582	0.324	-32.673	***						
1	PriceDisc	1.088	0.481	2.263	**	210.255	***	7	10.929	*	6
2	PriceDisc	1.998	0.415	4.809	***						
3	PriceDisc	2.601	0.406	6.408	***						
4	PriceDisc	1.667	0.184	9.059	***						
5	PriceDisc	2.317	0.682	3.395	***						
6	PriceDisc	3.345	0.848	3.943	***						
7	PriceDisc	2.055	0.453	4.538	***						
1	AssrtDisc	2.311	0.468	4.938	***	46.608	***	7	32.375	***	6
2	AssrtDisc	0.368	0.445	0.826							
3	AssrtDisc	0.064	0.415	0.155							
4	AssrtDisc	0.226	0.193	1.171							
5	AssrtDisc	0.015	0.677	0.022							
6	AssrtDisc	-1.409	0.912	-1.546							
7	AssrtDisc	1.961	0.477	4.113	***						
1	AdvDisc	-0.117	0.226	-0.516		8.217		7	5.702		6
2	AdvDisc	-0.034	0.159	-0.216							
3	AdvDisc	-0.043	0.155	-0.276							
4	AdvDisc	-0.142	0.069	-2.052	**						
5	AdvDisc	-0.584	0.325	-1.795	*						
6	AdvDisc	0.366	0.418	0.875							
7	AdvDisc	0.097	0.161	0.603							
1	DV (lag)	11.145	0.233	47.867	***	46456.436	***	7	4899.195	***	6
2	DV (lag)	16.688	0.342	48.787	***						
3	DV (lag)	11.662	0.311	37.552	***						
4	DV (lag)	23.812	0.125	189.890	***						
5	DV (lag)	16.211	0.350	46.260	***						
6	DV (lag)	9.748	0.607	16.063	***						
7	DV (lag)	11.115	0.307	36.245	***						
	Quarter 1	0.382	0.122	3.138	***	51.263	***	3			
	Quarter 2	0.450	0.121	3.732	***						
	Quarter 3	-0.049	0.119	-0.412							
	Quarter 4	-0.783	0.119	-6.577	***						

***$p < .01$; **$p < .05$; *$p < .1$.
Notes: 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	0.123	206.259	***	42542.772	***	1			
	State 1	26.622	0.258	103.183	***	11716.906	***	6			
	State 2	-4.042	0.256	-15.769	***						
	State 3	-6.623	0.256	-25.862	***						
	State 4	1.235	0.135	9.175	***						
	State 5	-1.597	0.239	-6.688	***						
	State 6	-8.502	0.524	-16.227	***						
	State 7	-7.094	0.244	-29.125	***						
1	PricePLDisc	2.326	0.221	10.508	***	503.559	***	7	35.350	***	6
2	PricePLDisc	1.554	0.263	5.917	***						
3	PricePLDisc	2.584	0.266	9.717	***						
4	PricePLDisc	1.393	0.115	12.077	***						
5	PricePLDisc	2.237	0.319	7.018	***						
6	PricePLDisc	3.013	0.599	5.032	***						
7	PricePLDisc	1.330	0.274	4.860	***						
1	AssrtPLDisc	0.344	0.224	1.535		55.734	***	7	39.786	***	6
2	AssrtPLDisc	0.469	0.269	1.742	*						
3	AssrtPLDisc	0.278	0.265	1.049							
4	AssrtPLDisc	0.210	0.110	1.911	*						
5	AssrtPLDisc	-0.464	0.275	-1.691	*						
6	AssrtPLDisc	-1.154	0.578	-1.997	**						
7	AssrtPLDisc	1.681	0.278	6.043	***						
1	AdvPL	0.340	0.108	3.151	***	15.863	**	7	10.290		6
2	AdvPL	0.203	0.146	1.394							
3	AdvPL	0.148	0.155	0.956							
4	AdvPL	0.073	0.061	1.189							
5	AdvPL	-0.120	0.199	-0.604							
6	AdvPL	-0.037	0.348	-0.108							
7	AdvPL	-0.172	0.152	-1.132							
1	DV (lagged)	11.201	0.179	62.451	***	43244.400	***	7	3812.236	***	6
2	DV (lagged)	13.651	0.283	48.186	***						
3	DV (lagged)	9.028	0.246	36.642	***						
4	DV (lagged)	18.861	0.109	173.103	***						
5	DV (lagged)	12.163	0.249	48.932	***						
6	DV (lagged)	8.348	0.570	14.635	***						
7	DV (lagged)	8.478	0.252	33.636	***						
	Quarter 1	0.648	0.097	6.695	***	130.487	***	3			
	Quarter 2	0.350	0.097	3.590	***						
	Quarter 3	0.037	0.096	0.381							
	Quarter 4	-0.783	0.119	-6.577	***						

***$p < .01$; **$p < .05$; *$p < .1$.

Notes: 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	0.077	151.922	***	23080.312	***	1			
	State 1	-7.186	0.115	-62.660	***	9282.809	***	6			
	State 2	6.785	0.120	56.531	***						
	State 3	-6.087	0.112	-54.262	***						
	State 4	-3.980	0.075	-52.901	***						
	State 5	-7.466	0.120	-62.345	***						
	State 6	23.886	0.303	78.811	***						
	State 7	-5.952	0.113	-52.684	***						
1	PricePLSup	-0.195	0.092	-2.111	**	16.939	**	7	16.035	**	6
2	PricePLSup	-0.143	0.190	-0.751							
3	PricePLSup	0.050	0.126	0.400							
4	PricePLSup	-0.086	0.051	-1.695	*						
5	PricePLSup	0.056	0.129	0.432							
6	PricePLSup	-0.185	0.403	-0.459							
7	PricePLSup	0.375	0.125	2.991	***						
1	AssrtSup	-0.058	0.086	-0.675		74.896	***	7	71.240	***	6
2	AssrtSup	1.149	0.197	5.825	***						
3	AssrtSup	0.328	0.127	2.589	***						
4	AssrtSup	0.133	0.051	2.625	***						
5	AssrtSup	-0.120	0.113	-1.065							
6	AssrtSup	2.782	0.368	7.568	***						
7	AssrtSup	-0.119	0.126	-0.947							
1	AdvPL	-0.029	0.055	-0.529		7.288		7	7.213		6
2	AdvPL	-0.052	0.118	-0.438							
3	AdvPL	-0.202	0.099	-2.050	**						
4	AdvPL	0.015	0.037	0.403							
5	AdvPL	0.011	0.095	0.116							
6	AdvPL	-0.352	0.253	-1.393							
7	AdvPL	0.084	0.090	0.935							
1	DV (lagged)	2.873	0.102	28.163	***	29682.669	***	7	6563.606	***	6
2	DV (lagged)	8.621	0.090	96.223	***						
3	DV (lagged)	3.980	0.088	45.203	***						
4	DV (lagged)	7.631	0.048	158.300	***						
5	DV (lagged)	2.044	0.130	15.714	***						
6	DV (lagged)	9.400	0.243	38.694	***						
7	DV (lagged)	3.397	0.116	29.403	***						
	Quarter 1	0.052	0.043	1.195		2.131		3			
	Quarter 2	-0.040	0.043	-0.928							
	Quarter 3	0.017	0.043	0.398							
	Quarter 4	-0.029	0.043	-0.673							

***$p < .01$; **$p < .05$; *$p < .1$.

Notes: 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	0.136	182.176	***	33187.946	***	1			
	State 1	-9.033	0.241	-37.459	***	6864.709	***	6			
	State 2	-2.795	0.255	-10.951	***						
	State 3	-8.791	0.272	-32.332	***						
	State 4	0.681	0.158	4.304	***						
	State 5	5.250	0.303	17.354	***						
	State 6	-7.578	0.538	-14.090	***						
	State 7	22.266	0.353	63.058	***						
1	PricePromo	1.287	0.209	6.147	***	778.307	***	7	167.157	***	6
2	PricePromo	1.896	0.272	6.970	***						
3	PricePromo	0.904	0.274	3.304	***						
4	PricePromo	1.757	0.118	14.850	***						
5	PricePromo	4.875	0.330	14.779	***						
6	PricePromo	1.181	0.685	1.724	*						
7	PricePromo	4.267	0.327	13.035	***						
1	DV (lagged)	9.936	0.247	40.207	***	28912.398	***	7	1639.597	***	6
2	DV (lagged)	13.940	0.275	50.768	***						
3	DV (lagged)	8.810	0.299	29.498	***						
4	DV (lagged)	17.410	0.131	133.216	***						
5	DV (lagged)	13.851	0.306	45.315	***						
6	DV (lagged)	8.732	0.613	14.238	***						
7	DV (lagged)	8.122	0.288	28.167	***						
	Quarter 1	-0.014	0.112	-0.127		119.050	***	3			
	Quarter 2	-1.104	0.112	-9.834	***						
	Quarter 3	0.318	0.112	2.841	***						
	Quarter 4	0.800	0.111	7.192	***						

***$p < .01$; **$p < .05$; *$p < .1$.

Notes: Coef. = coefficient, SE = standard error, DF = degrees of freedom.

ESSAY II: TRANSCENDING THE BOUNDARIES OF RELATIONSHIP MARKETING: HOW DIGITAL PLATFORMS CREATE VALUE AND SHAPE CONSUMERS' LIFEWORLD AND HABITUS

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ABSTRACT

Digital platforms have been important drivers of economic growth and the subject of myriad research activities. This article integrates the different platform concepts discussed in the marketing literature based on their locus of value creation and proposes a classification along two dimensions: Transactional digital platforms (TDPs) focus on facilitating exchanges and deliver primarily functional benefits to consumers. By contrast, relational digital platforms (RDPs) provide hedonic benefits and function as gateways into the consumer's *lifeworld* and *habitus*, effectively merging the previously separate brand and consumer spheres. Recent technological advances are fueling this development by allowing brands to algorithmically orchestrate value-creating interactions through digital interfaces along a never-ending consumer journey. The authors devise several platform design levers that brands can use to foster the platform-consumer envelopment. However, they also caution managers and regulatory entities against malign outcomes such as discrimination and manipulation, which become increasingly subtle as traditional boundaries of relationship marketing are dissolved. Marketing's role as an advocate of the consumer is more important than ever in this technology-driven playing field.

Keywords: Digital platforms, relationship marketing, value creation, lifeworld

1 Introduction

Digitalization has been blurring consumers' physical and virtual worlds at an astonishing pace. Daily routines increasingly involve connected devices that digitalize, record, and transmit consumer's every action—from reading news in an online outlet, tracking and sharing work-outs with wearables, to ambient interactions with smart home appliances that digitalize the flick of a switch, doing the laundry, and brewing a coffee (Hoffman and Novak 2018). These activities continuously evolved from one-way read-only interactions in the 1990s to today's symbiotic web, in which consumers connect in a multitude of ways with each other, third-parties, and algorithms (Steinhoff et al. 2019).

This technological progress eliminates boundaries that traditionally have confined the relationship between brands and consumers to a limited number of touchpoints and a narrow, largely commercial scope. In a world of social networks, mobile and wearable devices, smart and connected homes, voice assistants and chatbots, customer touchpoints have become multifaceted, omnidirectional, and omnipresent. This plethora of new digital channels offers companies a direct gateway into consumers' daily lives. Thus, the interface to the consumer and competition over its dominance are more open than ever (Reinartz, Wiegand, and Imschloss 2019).

A versatile tool in the battle for the consumer interface are digital platforms, which bundle and orchestrate various activities under one roof and provide companies with a direct link to the end consumer (Boudreau 2017). In practice and literature, numerous platform types have been established, such as marketplaces (e.g., eBay, Amazon) or forums (e.g., Stack Overflow). While many of these platforms focus on facilitating exchanges between two market sides, a new relational type of platform has emerged that creates value through ongoing interactions with consumers beyond the initial purchase (e.g., Ramaswamy and Ozcan 2018). Such platforms have the potential to intensify brand engagement and the frequency and depth of interactions with consumers (Ramaswamy and Ozcan 2016).

These developments are not news to marketers and academics. However, and this is our main proposition, they have significant economic and sociological consequences. We demonstrate that digital platforms use new interfaces, data sources, and analytics to create unique value for consumers. This is tearing down the boundaries between brand and consumer, transforming their relationship from a series of discrete brand-centric interactions to a habitual, consumer-centric symbiosis, an almost unnoticed integration of the brand into the consumer's lifeworld. This makes such platforms increasingly indispensable and influential (Hoffman and Novak 2018). In this paper, we discuss how digital platforms transcend common relationship marketing practices, with far-reaching implications for companies, consumers, and society. Specifically, we address the following research questions:

(1) How do digital platforms create value for consumers and how do these values enable their blending with consumers' lifeworld and habitus?

(2) How can companies leverage platform design to *shape* consumers' lifeworld and habitus?

By addressing these research questions, this paper makes three main contributions. First, while much research on digital platforms has emerged in recent years, a comprehensive view does not exist. Rather, each study tends to focus on specific types of platforms, such as matchmakers (Wu, Zhang and Padmanabhan 2018), digital apps (Boyd, Kannan, and Slotegraaf 2019), or online brand communities (Huang, Tafti, and Mithas 2018). We integrate the fragmented literature, differentiate the various concepts, and classify them in a holistic framework. We propose a classification along two dimensions¬—transactional and relational value creation—that each give rise to four major sources of consumer value. Firms can use this framework to position their (prospective) offering in the platform universe and derive activities to strengthen this positioning. Second, we introduce the sociological concepts of lifeworld and habitus to the platform literature, which allow us to analyze how platforms transcend the boundaries between the brand and consumer spheres. This is a novel perspective that has only recently become conceivable through the advent of new digital interfaces and corresponding shifts in consumer behavior. Third, we combine the sociological theory of the colonization of lifeworlds (Habermas 1987) with a platform-design perspective to explicate how companies can actively shape consumer outcomes. In doing so, we combine insights from several literature streams (marketing, management, behavioral economics, information systems) to derive advice for companies seeking to transfer their offering beyond discrete exchanges and toward profound and perpetuated relationships.

This research builds on the concept of the Digitalized Interactive Platform (DIP) introduced by Ramaswamy and Ozcan (2018). The authors pose that by continuously engaging consumers with digital offerings through smart connected products, value creation becomes ongoing and multidirectional. We extend this intriguing idea along two important perspectives: First, we take a step back to systematize DIPs' value creation and relate it to other platform types. This allows us to develop a conceptual underpinning for different platform architectures by combining the anecdotally exemplified interactions to generalizable sources of value creation. Second—and using this understanding—we then develop the idea further, shedding light on the consequences of platform integration into consumers' daily lives. It is here that we can examine the platforms' potential to transcend the dichotomy of distinct brand-customer environments by the brand's entering of consumers' lifeworld and habitus and derive actionable recommendations for platform design choices.

2 Concepts of Digital Value Creation

Today's brands can choose among a variety of digital channels to interact with consumers. Accordingly, the academic and business literature have introduced numerous terminologies, leading to a fragmented and unclear landscape with often fuzzy and inconsistent definitions such as platforms, ecosystems, or branded apps. Table 1 summarizes the various terms discussed in the literature, their definitions, defining characteristics, and examples.

All of these digital channels aim at enabling and facilitating interactions within a brand's *ecosystem*, which describes the loose network of all relevant stakeholders being directly or indirectly connected with each other and the focal company (Gawer and Cusumano 2008). To manage this network, a *platform* can connect the company with one or more of its stakeholders and/or stakeholders with each other (Altman and Tushman 2017). Hence, platforms represent the digital infrastructure that mediates any of the interactions within a company's ecosystem. The involved parties fall into four categories: a) the platform owner(s), who own(s) the intellectual property of the platform, b) the platform provider(s), running the platform and controlling its interface with the user, c) platform producer(s) that offer products, services or content, and d) platform consumers that consume the offerings (Van Alstyne, Parker, and Choudary 2016). Importantly, the parties can take on several roles, that is, the same company may be the platform owner and provider while consumers can also take on the role of producers (Eckhardt et al. 2019; Van Alstyne, Parker, and Choudary 2016).

Multisided platforms (MSPs) represent a specific group of platforms that enable *direct* interactions between two or more *distinct* sides (Altman and Tushman 2017; Hagiu and Wright 2015). This definition implies that, first, the platform does not interfere with interactions but provides the infrastructure allowing parties to find and directly interact with one another. Second, demand and supply sides are clearly distinguishable during the exchange. *Digital marketplaces, matchmaking platforms,* and *knowledge exchange platforms* are common varieties of MSPs that meet this definition. Digital marketplaces are MSPs that strictly focus on commercial transactions between platform producers and consumers (Täuscher and Laudien 2018). Matchmaking platforms are MSPs whose value proposition rests upon providing matches between demand and supply (Wu, Zhang and Padmanabhan 2018), like dating sites or ride-hailing services. All platforms need to engage in matchmaking to some degree to ensure that consumers find the offering within an often vast assortment that best suits their needs. In the case of dedicated matchmaking platforms, however, the entire business model rests on algorithmically creating optimal matches (Wu, Zhang and Padmanabhan 2018). Finally, knowledge exchange platforms like Stack Overflow focus on knowledge sharing among users (Kuang et al. 2019).

Perren and Kozinets (2018) introduce another group of platforms denoted *lateral exchange markets* (LEMs), which partly overlap with MSPs. They define LEMs as markets created by a "platform that facilitates exchange activities among a network of *equivalently positioned* economic actors" (p. 21, accentuation ours). That is, regular consumers can assume the role of producers as well as consumers. For example, on eBay actors are equivalently positioned because consumers may act as both, sellers and buyers of products. The authors identify four distinct architectures of LEMs: *Matchmakers* simply connect consumers and producers, which interact directly with each other. Contrary to the previously discussed matchmaking platforms, matchmakers in the LEM context only feature equivalently positioned actors, as is the case for services from the sharing economy (Eckhardt et al. 2019). *Enablers* focus on providing platform producers with the tools to exchange their offerings with consumers. Exchanges in *hubs* are largely controlled by the platform, and the extent of direct interactions between consumers and producers is limited. *Forums* allow direct interaction between consumers and producers without any platform intermediation (Perren and Kozinets 2018). Contrary to knowledge exchange platforms, they may feature commercial transactions (Perren and Kozinets 2018).

Table 1: Overview of Platform Concepts

Terminology	Definition	Core Characteristics	Example
Ecosystems	"Ecosystems organize and leverage external entities, which are frequently complementors and have interdependencies between them" (Altman and Tushman 2017, p. 180).	The collection of interdependent parties that engage in value-creating interactions.	Apple's smartphone ecosystem
Platforms	"Platforms sit at the nexus of a multiple relationships to orchestrate value-creating interactions" (Boudreau 2017, p. 228).	A central organ that orchestrates value-creating interactions.	Any of the following.
Multi-Sided Platforms (MSPs)	"A two-sided market is one in which 1) two sets of agents interact through an intermediary or platform, and 2) the decisions of each set of agents affects the outcomes of the other set of agents" (Rysman 2009, p. 125).	Platform enables direct interactions between two distinct market sides.	Apple's Appstore,
Digital Marketplaces	"Marketplaces […] enable and support transactions between independent supply- and demand-side participants" (Täuscher and Laudien 2018).	Focus on commercial transactions.	Amazon Marketplace
Matchmaking Platforms	"[A] two-sided market" (Wu, Zhang and Padmanabhan 2018, p. 398) that "provide[s] matchmaking services that help customers find compatible partners" (p. 406).	The matchmaking technology is the platforms key value proposition.	Airbnb, Uber
Knowledge Exchange Platforms	"[I]ndividuals can simultaneously share their knowledge, experience, and expertise by answering questions and posting articles" (Kuang et al. 2019, p. 290).	Exchange of knowledge between equally positioned actors.	Stack Overflow, Quora.com
Lateral Exchange Markets (LEMs)	"[A] market that is formed through an intermediating technology platform that facilitates exchange activities among a network of equivalently positioned economic actors" (Perren and Kozinets 2018, p. 21).	Platform producers and consumers are equivalently positioned.	Ebay, Uber, Airbnb
Sharing Economy	"[A] technologically enabled socioeconomic system with five key characteristics (i.e., temporary access, transfer of economic value, platform mediation, expanded consumer role, and crowd-sourced supply)" (Eckhardt et al. 2019, Abstract).	Ownership temporary and mediated by a matchmaker. Platform consumers are also producers.	BlaBlaCar, LendingClub
Branded Apps	"[S]oftware downloadable to a mobile device which prominently displays a brand identity […] throughout the user experience" (Bellman et al. 2011, p. 191).	Enables direct interactions between brand and customers.	Nivea App
Online Brand Communities	"[A] group of ardent consumers organized around the lifestyle, activities, and ethos of the brand" (Fournier and Lee 2009, p. 2).	Brand-related knowledge sharing among customers.	Harley-Davidson Community
Virtual Customer Environments (VCEs)	"[P]rovide services ranging from online discussion forums to virtual design and prototyping centers, enable firms to involve their customers in product design, product testing, and product support activities" (Nambisan and Baron 2009, p. 389).	Platform-customer interactions focused on co-innovation.	SAP Co-Innovation Lab
Brand Engagement Platforms (BEPs)	"[A]ny physical/digital interactional assemblage of persons […], artifacts (including data), interfaces, and processes, whose design intensifies agencial engagement" (Ramaswamy & Ozcan 2014, p. 96).	Designed to intensify brand engagement, e.g. in the form of co-creation, of a brand's stakeholders.	L'Oréal Style My Hair
Digitalized Interactive Platforms (DIPs)	"[A]n evolving digitalized networked arrangement of artifacts, persons, processes, and interfaces […] one where value is created through interactions, versus one where value is simply the exchange of a fixed offering" (Ramaswamy and Ozcan 2018, p. 19).	Creates value through *interactions* on the platform instead of exchanges of products or services.	Apple Watch NikePlus

While MSPs and LEMs center on orchestrating interactions between different stakeholders in the focal brand's ecosystem, platform types also exist that focus on direct interactions between the brand and its customers. For example, *branded apps*, i.e. mobile applications provided by a brand, are described in the literature as systems for consumers to engage in self-service activities, shopping, or brand-related social interactions (Boyd, Kannan, and Slotegraaf 2019). *Online brand communities* are often owned and managed by brands connecting consumers around "the lifestyle, activities, and ethos of the brand" (Fournier and Lee 2009, p. 2), enabling them to share their knowledge of the brand, its products, and applications (Huang, Tafti, and Mithas 2018; Schau, Muniz, and Arnould 2009). *Virtual Customer Environments* (VCEs) represent various platform designs that involve customers in the brand's product development process, for example in terms of product testing, co-innovation, and co-design (Nambisan and Baron 2009).

Ramaswamy and Ozcan (2016; 2018) introduce a novel, marketing-focused perspective on platforms. Their concept of *Brand Engagement Platforms* (BEPs) introduces a platform type that allows and encourages consumers to interact with each other, the brand, and third parties in a joint creation of experience and value (Ramaswamy and Ozcan 2016). In their concept of *Digitalized Interactive Platforms* (DIPs), the authors enhance this notion, arguing that DIPs allow brands to extend their activities beyond a simple "exchange of a fixed offering between a firm and its customers" (Ramaswamy and Ozcan 2018, p. 19) and instead to create value through interactions between the platform components. These components consist of *artifacts* (data), *persons* (platform participants), *processes* (mechanisms and algorithms), and *interfaces* (digital and physical touchpoints like apps, websites, wearables) (Ramaswamy and Ozcan 2018). Recent technological advances have affected and will continue to affect each of the four platform components, further enhancing the creation of value: Today's brands can collect, store, analyze, and transmit a myriad of data points (artifacts), personalize interactions through algorithms (processes), connect with consumers through ambient devices (interfaces), and allow integration of participants through standardized APIs (persons). While Ramaswamy and Ozcan (2018) focus on interactions among these components, we assume a value-creation perspective, which allows us to examine how these platforms are able to build profound and ongoing brand-consumer relationships, merging the previously separate worlds.

3 Two Dimensions of Value Creation

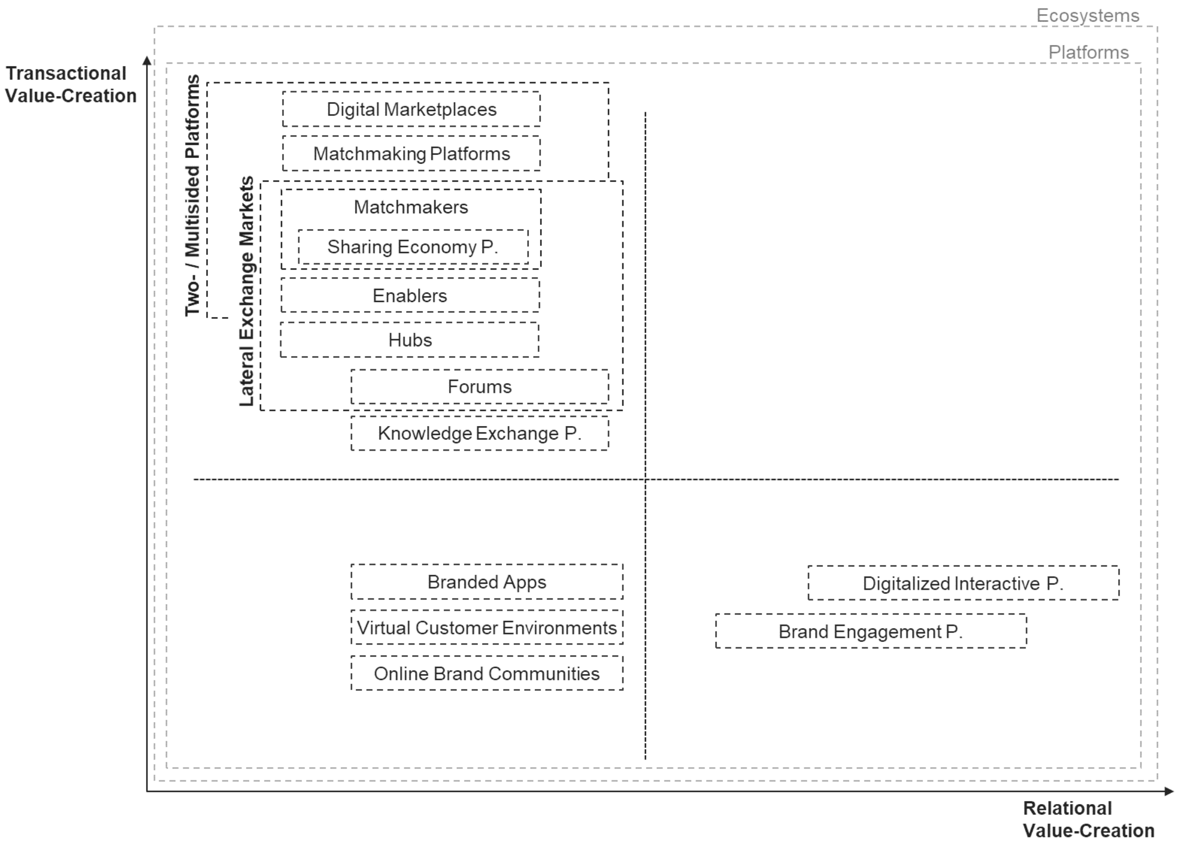
Our literature review on platforms provides an overview and clarification of the manifold terminologies used by researchers and practitioners. In the following, we analyze and cluster the platform types in terms of their locus of value creation for consumers. We demonstrate that two fundamental dimensions of value exist that differentiate the various platform types described above. These two dimensions help academics and managers understand the ways in which platforms create value for consumers and, thereby, reveal two paths to platform success.

MSPs, LEMs, and their varieties may have distinct characteristics, but the interactions are all exchange-focused. Whether a commercial transaction takes place in a digital marketplace, an entrepreneur looks for investors on a crowdfunding platform, or a researcher posts a question on a knowledge exchange platform: All of these interactions are primarily exchange-based and finished once the exchange is completed. From a consumer perspective, the locus of value is thus created by the exchange itself and the transferred product or service (Holbrook 1999; Khalifa 2004; Vargo and Lusch 2004). Given this focus on value-in-exchange, interactions beyond the purchase stage are limited as these platforms primarily address consumers' functional needs and immediate consumption-related goals (Lusch and Vargo 2006; Park, Jaworski, and MacInnis 1986). Interactions on the platform have a clear starting point at the moment of need recognition and the formation of consumption intentions (Huffman, Ratheshwar and Mick 2003; Ratneshwar, Pechmann and Shocker 1996) and end with the successful transaction. We thus call this family of platforms *transactional digital platforms* (TDPs).

By contrast, BEPs and DIPs create the locus of value for consumers through ongoing interactions among the platform provider, producers, and consumers (Ramaswamy and Ozcan 2018). Hence, the value-creation process resembles the value-in-use concept brought forward by the service-dominant logic (Vargo and Lusch 2004). On these platforms, the consumer plays an active part in the interactions and accordingly co-creates the experience (Prahalad and Ramaswamy 2004). While value creation on TDPs is mainly functional, economic, and utilitarian in nature, we propose that these platforms create several other types of value discussed in the literature, especially experiential, hedonic, social and epistemic value (Park, Jaworski, and MacInnis 1986; Sheth, Newman and Gross 1991; Smith and Colgate 2007). Contrary to TDPs, value creation is not restricted to a specific consumption need and the associated transaction but rather covers the entire relationship continuum. These extend to all platform participants (provider, consumers, and producers) and components (artifacts, persons, processes, and interfaces). For example, a consumer may use UnderArmour's fitness app to run a route shared by a friend, receive feedback from the platform's AI-powered coach, and enjoy content provided by the celebrities present on the platform. Value creation thus extends even beyond the value-in-use perspective (Lusch and Vargo 2006; Ramaswamy and Ozcan 2018). "[O]fferings are no longer 'finished'" (Ramaswamy and Ozcan 2018, p. 19) but extended through ongoing interactions. Hence, consumers do not use these platforms in individual, potentially repeated exchanges but throughout a perpetuated relationship. We therefore call these platforms *relational digital platforms* (RDPs).

Our clustering of platform types based on their locus of value creation thus reveals two underlying dimensions, transactional and relational value creation, which we use to structure the platform universe (Figure 1).

Figure 1: Concepts of Transactional and Relational Value Creation



Some platform types discussed in the literature exhibit both transactional and relational features. For example, branded apps, VCEs, and online brand communities may enable purchases, implement interactive co-innovation systems or social features. However, these interactions are limited to the issuing brand and, therefore, lack the breadth of MSPs and LEMs, which offer access to different platform producers. Likewise, relational interactions are confined to the issuing brand, excluding third parties, and feature an often company-serving, narrow scope such as co-innovating a specific product. Hence, these platform types typically score low in terms of both transactional and relational value.

TDPs represent the more traditional view on platforms that originated in the economics literature and focuses on the intermediation of two market sides (e.g. Rochet and Tirole 2003). In this way, their value creation resembles the product-centric orientation of companies prevailing in the 1950s and ’60s (Sheth, Sisodia and Sharma 2000). TDPs usually make up the first wave of platforms in a sector's digital marketplace. Examples are Amazon in consumer products, Airbnb in accommodation, and Uber in transportation. Just as companies gradually adopted a more customer- and relationship-centric approach over time (Sheth, Sisodia and Sharma 2000), platforms have become more relationally focused in recent years. Amazon, for example, has introduced community-like features through which users can manage own profiles, upload photos, and answer questions from other consumers. Airbnb complements its core offering with a variety of holiday activities, from city tours and cooking classes to organized journeys.

While this breed of companies was born into the digital marketplace, traditional, offline-focused companies are also embracing the digital environment—not just as a marketing or sales channel but as a distinct playing field with unique value-creation opportunities. Dutch brewing company Heineken launched Beerwulf, a TDP through which it sells craft beers from small breweries but also brands owned by direct competitors, Clos19 is a TDP through which the LVMH Group sells many of its brands, such as Hennessy and Moët, directly to consumers, and Siemens brings together its business consumers with third party spare parts suppliers. On the relational side, the most sophisticated RDPs stem from the health and fitness sector with Adidas' Runtastic, Nike's NikePlus, and UnderArmour's Connected Fitness, which allow consumers to interact with AI-powered coaches and a community of consumers and celebrities. Other examples for RDPs have emerged in the automobile sector such as Mercedes Me, which provides consumers with content, third-party services, and suggestions for trips and scenic routes.

As evident from Figure 1, a term for platforms situated in the upper right corner has not yet emerged. This may stem from the fact that only few brands occupy this area. WeChat is one of these rare examples, with a mind-boggling number of features such as access to a large variety of third-party offerings, appointment booking, community features, and investment and personal finance management. In the coming years, we expect more of these platforms to emerge, especially through established TDPs incorporating relational aspects and RDPs adopting transactional components.

3.1 Transactional Value Creation

We propose that by bringing together parties and enabling their exchange, TDPs create value for consumers in four major ways: They (1) offer a broad *assortment*, (2) *match* supply and demand, (3) provide *information* on platform producers, consumers, and offerings, and (4) ensure a smooth and convenient *fulfillment* of the exchange. We discuss each of these transactional value components in the following.

Assortment Value. Driven by (indirect) network effects, TDPs can attract a large number of consumers and suppliers through a positive feedback loop in which additional consumers draw more producers to the platform and vice versa (Chu and Manchanda 2016; Katz and Shapiro 1994). Digitization considerably boosts these network effects because it lifts physical and temporal constraints, allowing the platform to accommodate a virtually infinite number of consumers and producers irrespective of their physical location. Hence, consumers can enjoy an assortment that is wider and deeper than that of any classical online or offline retailer (Alba et al. 1997)—a fundamental source of value creation. Airbnb, for example, offers more accommodations than the major hotel chains combined (Hartmans 2017). The assortment value allows consumers to find precisely the offering they are looking for, thus minimizing the need to compromise (Brynjolfsson, Hu and Smith 2003; Hoch, Bradlow and Wansink 1999), allowing for one-stop shopping, and reducing transaction costs (Messinger and Narasimhan 1997).

Matchmaking Value. The assortment, however, is of little use, if consumers incur high search costs to find the offering that suits their needs. Especially if assortments are increasingly deep and wide, consumers can feel cognitively overwhelmed and fear to make the wrong choice

(Gourville and Soman 2005; Xu, Jing, and Dhar 2013). Moreover, the assortment may simply become too crowded to properly process (Huffmann and Kahn 1998) while also inflating consumers' expectations (Diehl and Poynor 2010). As large assortments are of little worth without search functionalities, platforms employ matchmaking mechanisms that ensure consumers find the desired offering without an escalation of search costs. These matchmaking mechanisms may require active consumer input, as in the case of search boxes, ratings, and filters. Other approaches rely on machine learning methods that leverage data on past consumer behavior, such as automated recommender systems (Lee, Kim and Rhee 2001) and content curation mechanisms (Lazer 2015). Prior research shows that successful matchmaking increases the consumption of niche products in online vis-à-vis offline transactions, indicating that matchmaking not only reduces search costs but allows consumers to discover the very offering that best satisfies their idiosyncratic need (Brynjolfsson, Hu, and Simester 2011).

Information Value. TDPs feature information on the products and services they offer. This information may be provided by (1) the respective platform producers (e.g. price and product attributes), (2) the platform provider (e.g. a product's sales rank), or (3) the platform consumers, for instance in form of product reviews and ratings. Especially the latter have been shown to substantially influence consumers' purchase decisions (Floyd et al. 2014). TDPs also provide information on the individual platform producers and consumers themselves, for example in terms of satisfaction ratings and reviews. Again, this information may be provided by any of the three platform parties and allows TDPs to function properly. It instills trust, incentivizes adherence to contractual obligations, prevents fraud, and alleviates asymmetric information (Hui et al. 2016; Roberts 2011), especially when the platform provider is agnostic towards producers' and consumers' a priori quality (Chu and Manchanda 2016).

Fulfillment Value. TDPs are mediators of exchanges and, therefore, can create value by providing a smooth and convenient fulfillment of the exchange. Convenience is achieved along five dimensions: access, search, evaluation, transaction, and post-purchase (Jiang, Yang, and Jun 2013). Platforms provide access convenience through their online accessibility and by being open to all consumers (Broekhuizen et al. 2019). They also offer search and evaluation convenience, which are reflected in the matchmaking and information values described above. Fulfillment value takes effect through transaction and post-purchase convenience. Transaction convenience is achieved, for example, by offering a variety of payment methods, a smooth check-out process, and additional features like Amazon's one-click buying or dash buttons (Jiang, Yang, and Jun 2013). Post-purchase convenience is realized, for example, through timely delivery, eco-friendly shipping options, as well as services that mitigate the risks associated with exchanges as shown in the previous paragraph. Platform providers may offer money-back guarantees, buyer protection programs (Hui et al. 2016; Roberts 2011), or handle product returns and conflicts between exchange parties (Jiang, Yang, and Jun 2013).

Successful TDPs deliver value along all four components. However, assortment value always lays the foundation that information, matchmaking, and fulfillment value build on (Chu and Manchanda 2016; Song et al. 2018). Their importance grows in relation to the assortment size, owing to the associated increase in crowdedness and quality discrepancies among offerings and producers. Matchmaking value reduces consumers' search costs. Information and fulfillment value assure that offerings align with expectations and that parties meet their contractual obligations. Platform growth is indispensable for TDPs, as the associated network effects attract further platform producers that increase the assortment value, while consumers provide more data that elevate matchmaking and information values (Van Alstyne, Parker, and Choudary 2016).

3.2 Relational Value Creation

We propose four value components that RDPs are able to create: (1) *customization* of the core offering, (2) *social* interactions, (3) assisting consumers in achieving personal goals (*self-actualization*), and (4) providing *hedonic* experiences. We explicate each in the following.

Customization value. RDPs can offer consumers customized solutions through two mechanisms: First, they complement core offerings with additional services, provided either by the platform provider or by external platform producers, which is commonly known as integrated solutions (Epp and Price 2011; Tuli, Kohli, and Bharadway 2007). This has been greatly facilitated through digitalization as third parties are not constraint by time or place and can use standardized interfaces (APIs) that ensure that third party offerings are deeply integrated into the value-creation process of the platform at low marginal costs (Reinartz, Wiegand and Imschloss 2019; Sheth, Sisodia and Sharma 2000). Second, through co-creation, consumers can tailor attributes of the core offering to match their unique requirements (Prahalad and Ramaswamy 2004). In doing so, consumers may not only create value for themselves but also for other consumers, for example by engaging in the development of new offerings (Etgar 2008; Nambisan 2002) or creating user-generated content (UGC). UGC represents an important source of value for consumers (Kohler et al 2011; Trusov, Bucklin and Pauwels 2009) and allows platforms to offer a large variety of content and customized services, which was previously only possible at high costs (Kumar and Reinartz 2016; Labrecque et al. 2013).

Social value. Social value relates to value derived from consumers' interactions with other platform participants such as consumers, third parties, or employees. Research on co-creation, brand communities, and website usage shows that the associated social interactions lead to various psychological benefits for consumers (e.g. Nambisan and Baron 2009). They create a sense of belonging and social identity (Schau, Muniz, and Arnould 2009; Xie, Bagozzi and Troye 2008). Additionally, consumers enjoy the status, reputation, and esteem they build within a community of peers as well as expressing a unique self-image, which gives them a sense of self-efficacy (Holbrook 1999; Nambisan and Baron 2009). Consumers may achieve these benefits on the platform through a variety of means, for example by sharing experiences and knowledge (Wasko and Faraj 2000), public badges or leaderboard rankings (Labrecque et al. 2013), or expressing personal beliefs (Hollenbeck and Kaikati 2012; Marder et al. 2016).

Self-actualization value. Consumers have the fundamental urge to self-actualize, that is, to live up to their full potential, "the desire to become more and more what one is, to become everything that one is capable of becoming" (Maslow 1943, p. 93; see also Csikszentmihalyi 2000). Prior literature has incorporated individual aspects of self-actualization value in terms of acquiring knowledge, specifically epistemic value (Sheth, Newman, and Gross 1991), excellence (Holbrook 1999), cognitive and personal integrative benefits (Nambisan and Baron 2009), as well as symbolic needs (Park, Jaworski, and MacInnis 1986). We extend this concept to include additional aspects of self-actualization such as self-respect and accomplishment (Holbrook 1999; Xie, Bagozzi, and Troye 2008). These are underlying today's self-quantification and self-improvement trends which are addressed in many RDPs, especially in the context of fitness, health, or nutrition. Its development is fueled by the widespread use of connected devices such as mobile phones and wearable devices that are capable of tracking and quantifying consumers' daily lives and activities, workouts, sleep quality, heart rate, and more (James, Deane and Wallace 2019). The culmination of this development is the concept of the quantified self, which aims at data-based self-improvement (Kelly 2016; Wolf 2010). Through ongoing interactions with consumers, RDPs are able to provide educational content, performance and progress quantification, and personalized advice that collectively assist consumers in their pursuit of self-actualization.

Hedonic value. Finally, RDPs provide consumers with hedonic value, which may come in the form of content provided for consumers' pleasure or escapism (Holbrook 1999;

Nambisan and Baron 2009; Sheth, Newman, and Gross 1991) and which serves their experiential needs (Park, Jaworski, and MacInnis 1986). In addition, many platforms provide games and gamification features such as the ability to win virtual points through repeated interactions (Hofacker et al. 2016; Shankar et al. 2016). Hedonic experiences are traditionally less intense online than offline (Grewal, Levy, and Kumar 2009; Verhoef et al. 2009). However, more powerful devices and new technologies are enabling increasingly engaging digital experiences, especially through virtual and augmented reality (VR, AR) systems (Reinartz, Wiegand and Imschloss 2019).

Similar to TDPs, the most successful RDPs such as UnderArmour's Connected Fitness create value along all four components and thereby are able to transcend from an individual exchange focus to a perpetuated relationship focus. Self-actualization represents the pinnacle of the four components, addressing consumers' long-term goals and, therefore, allowing RDPs to interact with consumers along their journey of attaining these goals. We elaborate on this aspect subsequently. Just as TDPs, RDPs profit from network effects. Additional producers and consumers elevate each of the four value components through complementary services, content, and interactions. The differences between TDPs' and RDPs' value components lead to distinct implications for management. TDPs need to attract producers that offer substitutes and thus directly compete with each other. To succeed, companies may need to dissociate themselves and their established brands from the platform as shown by Goldman Sachs: When it launched a TDP for financial products, other banks were reluctant to join the platform until it dissociated by selling shares to competitors (Hoffman 2018). RDPs, in contrast, incorporate third parties that provide complementary offerings. This means established companies can leverage their existing business connections to support their RDPs and build on their existing brands' strengths and installed customer base.

The value components also reveal that TDPs may instill high behavioral loyalty in consumers and generate a direct revenue stream. In contrast, RDPs create profound attitudinal loyalty and affect revenues in the long run. Hence, TDPs present an attractive strategy for sectors still undisrupted by platforms, whereas RDPs allow companies to win back market share from competitors' TDPs and are a crucial long-term strategy.

Using the value components, managers can optimize platform designs to reflect the intended strategic orientation. For example, a company that sets out to provide transactional value for its stakeholders needs to put emphasis on offering a wide and/or deep assortment, matchmaking mechanisms, reliable information, and fulfillment enhancing options such as guarantees. To strengthen customer relationships, managers should add functionalities that empower consumers to co-create value, foster an active community, and provide educational and experiential content. The value components thus help managers to align their platform's feature set with strategic goals and to "tick off boxes", informing them how far they have already progressed on the respective value dimensions and which components their platform lacks.

While literature to date extensively discusses the competitive advantages of platforms and their success factors from a company perspective, for example in terms of its openness (Boudreau 2010), network effects (Afuah 2013), and governance structures (Perren and Kozinets 2018), it neglects a distinct consumer perspective on platforms. The two value dimensions and eight value components presented in Table 2 address exactly this literature gap, identifying the concrete factors that allow platforms to succeed in the marketplace.

Table 2: Platform Prototypes, Value Components, and Strategic Implications

		Transactional Digital Platforms (TDPs)			Relational Digital Platform (RDPs)	
Value Components & Related Concepts	**Transactional Value Creation**	• Efficiency & excellence (1) • Value exchange (4)	• Value-in-exchange (8) • Functional needs (5)	**Relational Value Creation**	• Value buildup (4) • Value-in-use (8)	• Experiential/hedonic & symbolic/expressive value (7)
	Assortment Value	• Functional value (6) • Functional/instr. value (7)	• Access convenience (2)	**Customization Value**	• Functional and conditional value (6)	
	Matchmaking Value	• Functional value (6) • Cost/sacrifice value (7)	• Search & evaluation convenience (2)	**Social Value**	• Status & esteem (1) • Symbolic needs (5)	• Social & personal integrative benefits (3)
	Information Value	• Functional/instr. value (7)	• Search & evaluation convenience (2)	**Self-Actualization Value**	• Excellence (1) • Epistemic value (6)	• Symbolic needs (5) • Cognitive benefits (3)
	Fulfillment Value	• Cost/sacrifice value (7)	• Transaction & post-purchase convenience (2)	**Hedonic Value**	• Play & aesthetics (1) • Emotional value (6)	• Experiential needs (5) • Hedonic & affective benefits (3)
Platform Components	**Artifacts**	• Information on offerings, consumers and producers • Actively provided by platform parties. • Provide information value.			• Variety of data points and sources, actively and passively transmitted. • Creates value in terms of insights (e.g. progress report) and content. • Provide customized, self-actualization and hedonic value.	
	Persons	• Consumers, potentially as producers (e.g. sharing economy). • Third-parties offering substitutes. • Provide assortment value and information value.			• Consumers as co-creators of content, services, and interactions. • Third-parties provide complementary offerings. • Provide social, hedonic, and customized value.	
	Processes	• Matchmaking and automated recommender systems. • Smooth convenient exchange process. • Reduce search costs and risks. • Provide matchmaking and fulfillment value.			• Enabling social interactions (e.g. messaging, sharing, content creation) • Co-creation functionalities • Automated data upload, generation of personalized insights and interactions • Content curation	
	Interfaces	• Usually read-write interfaces (e.g. apps, websites). • Few exceptions (e.g. Amazon Dash Buttons).			• High relevance of smart connected devices (e.g. wearables, smart home appliances).	
Strategic Implications		• Assortment value lays the foundation for matchmaking, information, and fulfillment value. • With growing platform size matchmaking, information and fulfillment value become increasingly important. • Companies may need to dissociate from their established brands to attract platform producers and consumers. • Repeated interactions form behavioral loyalty with direct revenue impact. • Suited for sectors without dominant TDP.			• Self-actualization constitutes the pinnacle of relational value creation by assisting consumers in their pursuit of goals. • Growing platform size elevates value components. • Companies can leverage existing business connections and build on existing brand strengths and their installed consumer base. • Ongoing interactions creating attitudinal loyalty through perpetuated relationships and indirect long-term revenue impact. • Suited for sectors with established TDPs.	

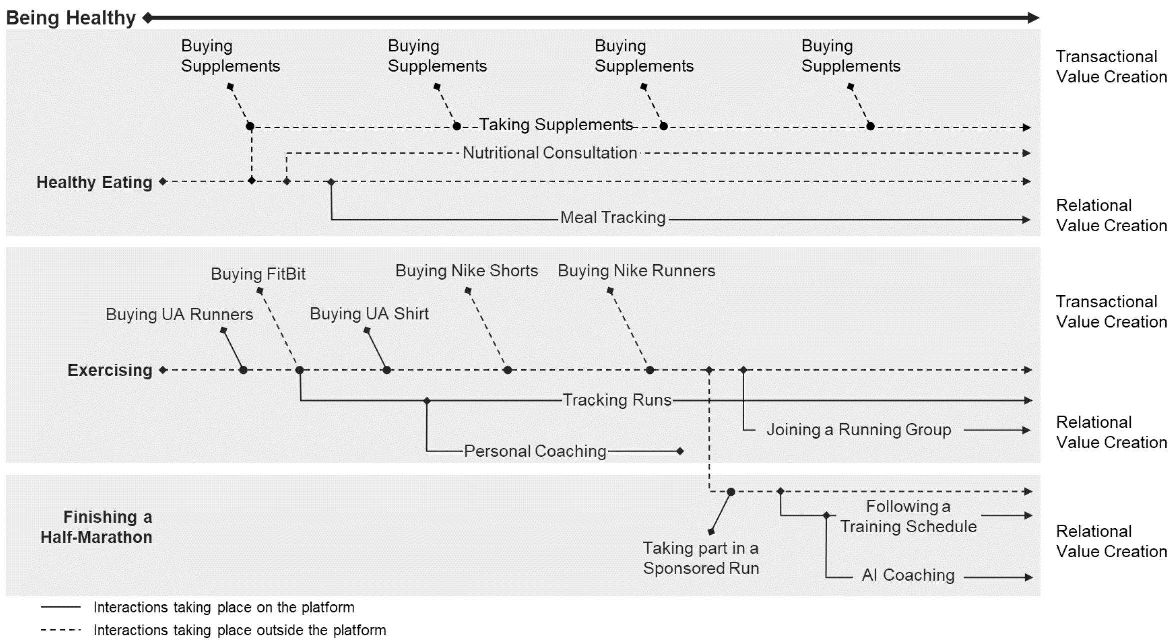
1) Holbrook 1999
2) Jiang, Yang, and Jun 2013
3) Nambisan and Baron 2009
4) Khalifa 2004
5) Park, Jaworski, and MacInnis 1986
6) Sheth, Newman, and Gross 1991
7) Smith and Colgate 2007
8) Vargo and Lusch 2006

4 Relational Digital Platforms: Towards Perpetual Value Creation

The previous discussion suggests that TDPs and RDPs create fundamentally different value for consumers and, thereby, address distinct consumer goals. According to means-end theory, literature views these goals as hierarchically organized, that is, based on a natural order that defines the relations between them (Huffman, Ratneshwar and Mick 2003; Pieters, Baumgartner and Allen 1995). On the highest level, consumers formulate abstract goals that describe why they perform certain actions in the pursuit of their personal values and ideal self-identity (Pieters, Baumgartner and Allen 1995), for example living sustainably (Belk 1988). These superordinate goals motivate specific focal goals that define a concrete target such as reducing one's CO_2 footprint (Belk 1988; Pieters, Baumgartner, and Allen 1995). On the lowest, subordinate level, consumers define actions and behaviors that allow them to achieve their higher-level goals, including purchases and the need for specific product attributes, like choosing a train ticket over a plane ticket (Belk 1988; Pieters, Baumgartner, and Allen 1995). Akin to this hierarchical view, Park, Jaworski, and MacInnis (1986) identify different types of consumer needs: Functional needs reside on a lower-level and relate to concrete consumption problems. They are followed by experiential and symbolic needs and the desire for hedonic experiences, self-actualization, self-identity, and sociality (Smith and Colgate 2007), which are more abstract in nature and never exhaustively satisfied (Park, Jaworski and MacInnis 1986).

TDPs address consumers' lower-level goals and needs by offering the previously discussed assortment, matchmaking, information, and fulfillment values. These TDP offerings are powerful indeed, explaining much of the dramatic rise of the platform model hereto. Continuing from there, RDPs are able to address higher-level goals and needs by providing customization, self-actualization, social, and hedonic value. Accordingly, they envelop a wide variety of consumers' subordinate goals and needs—including purchases—that are motivated by higher-level goals (Pieters, Baumgartner and Allen 1995). Consequently, RDPs can extend and prolong the interactions with consumers far beyond the boundaries of a typical customer journey. They create value for consumers along their pursuit of these higher-level goals and needs, which are never fully accomplished, as consumers strive to be or become someone, realizing their potential and nurturing their self-identity rather than performing individual actions (Huffman, Ratneshwar and Mick 2003; Pieters, Baumgartner and Allen 1995).

Figure 2: Higher- and Lower-Level Goal Structure



The structure of goals and associated behaviors, interactions, and transactions are represented in Figure 2, exemplary for the brand UnderArmour. Here, the consumer's overarching goal is health improvement, which motivates lower-level goals such as healthy eating and exercising. Each of these goals create consumption opportunities such as buying new running shoes or a tracking device. They also spur ongoing subordinate goals like tracking runs, coaching, or following a proposed training schedule through which the platform is able to interact with the consumer on an ongoing basis. As a consequence, offerings are not only "no longer 'finished'", as Ramaswamy and Ozcan (2018, p. 19) state, but extend beyond the brand's core value creation long after, long before, and even independent of an actual purchase through the perpetuation of value-creating interactions along various goals on different levels.

It is important to note that these ongoing interactions have only become possible as a result of recent technological advances. Consumers are "always on" via smartphones, wearable devices, smart home gadgets, and other interfaces. This means that platforms constantly receive consumer data, which allows them to personalize interactions. In the past, platforms had to rely on consumers to actively transmit data. Nowadays, data collection is increasingly passive with a large amount and variety of data points transmitted automatically by the connected devices. Furthermore, through advances in data management and analysis, especially in terms of the various machine-learning applications, interactions are no longer consumer-initiated but increasingly platform-initiated. That is, platforms autonomously trigger personalized interactions, for example through a push-notification on the consumer's smartphone, a vibration on their wearable device, or an announcement by a voice assistant. Additionally, advances in system integration and the ongoing digitization of information allow for the seamless integration of partners to a platform through standardized interfaces (APIs). Finally, technological advances improve the integration across online and offline channels and devices, leading to further blurring of the lines between separate touchpoints and towards an integrated, ongoing relationship. RDPs, therefore, create tighter bonds between brands and consumers than ever before as a result of their focus on addressing consumers' higher-level goals, enabled and fundamentally elevated through technological advances.

Lemon and Verhoef (2016) argue that, in theory, a consumer's prepurchase stage encompasses her entire experiences before purchase, starting with her very first "need/goal/impulse" (p. 76). Similarly, the post-purchase stage theoretically extends to the end of a customer's life (Lemon and Verhoef 2016). RDPs are getting ever closer to these theoretical boundaries of the customer journey and may transcend them soon. Whereas the classical journey forms around a purchase incidence, RDPs create value independent of a purchase, transforming the *customer* journey into a *consumer* journey, in which the relational platform envelops consumers' pursuit of various goals, actions, and potentially transactions. The platform develops into a constant companion, gradually claiming larger parts of the consumers' activities. This view goes far beyond classical marketing communication and customer relationship management which center on singular touchpoints. RDPs introduce ongoing and evolving interactions of very diverse nature between brands and consumers, which calls for a sociological perspective of analysis in order to determine how this evolution affects consumers. We propose that RDPs' envelopment of consumers' goals and activities allows them to become part of and significantly shape consumers' *lifeworlds* and *habitus*. We elaborate on this proposition and discuss the potential consequences of this development in the following.

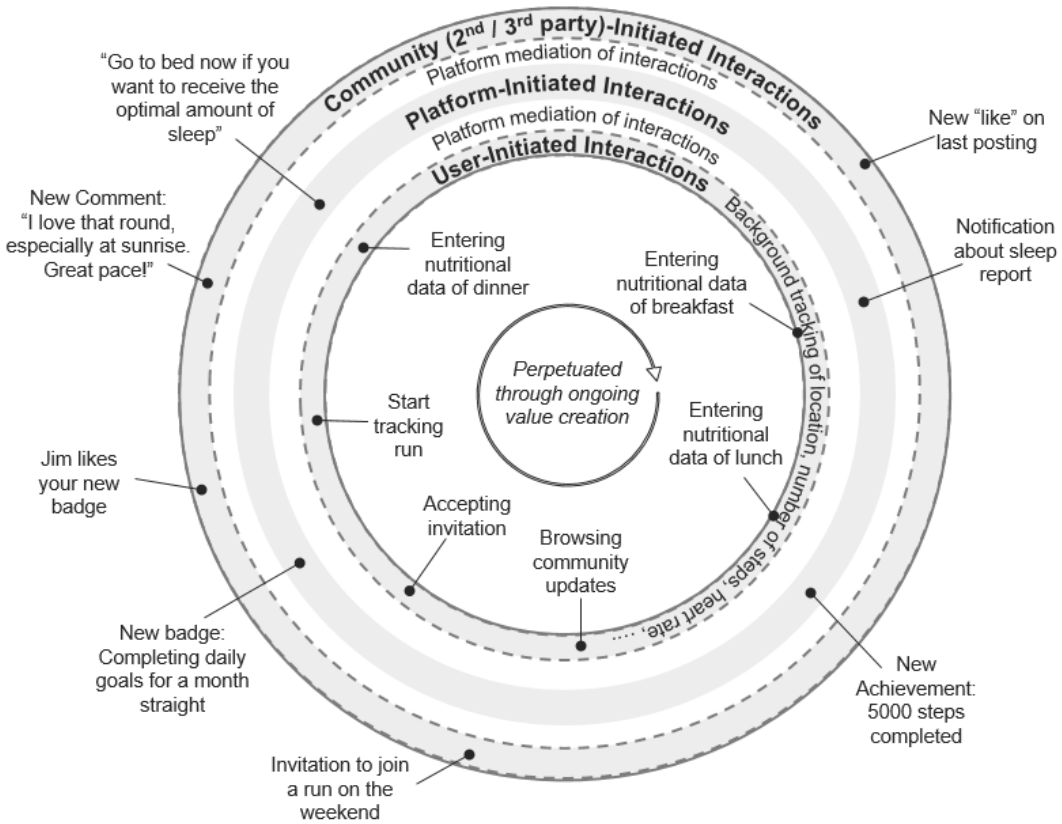
5 Entering and Shaping Consumers' Lifeworlds and Habitus

Lifeworld is a fundamental concept of phenomenological research going back to Edmund Husserl (1936), which has been widely adopted by sociology and anthropology (Giddens 1991; Schutz 1970). It takes a subjective view on the environment a person inhabits, describing how she lives in and experiences it, that is, "[t]he total sphere of experiences of an individual which is circumscribed by the objects, persons, and events encountered in the pursuit of the pragmatic objectives of living" (Schutz 1970, p. 320). These encounters are not necessarily physical but also include digital and otherwise mediated experiences, a point already raised by Schutz and Luckmann (1973). As brought forward by Ramaswamy and Ozcan (2016), platforms consist of artifacts, interfaces, persons, and processes, in other words, the very objects (artifacts and interfaces), persons, and events (processes) that Schutz (1970) identified as building blocks of consumers' lifeworlds. However, not all encounters become part of one's lifeworld. Infrequent, meaningless encounters do not inform consumers' experiences and, therefore, enter the lifeworld only peripherally and non-permanently (Atkinson 2010).

Interestingly, most of a company's insular consumer-directed interactions and traditional marketing activities fall into this category. To a large degree, they remain meaningless because they are not lasting, not personal, and not valuable. Not being able to create true meaning has been exactly traditional marketing's long unresolved puzzle. Instead, the *continuous* encounters *"in the pursuit of the pragmatic objectives of living"* (Schutz 1970, p. 320), the "*everyday experiences*" (Atkinson 2010, p. 9) do build into a consumers' lifeworld—these are precisely the types of perpetuated interactions that RDPs engage consumers in.

Continuing our previous example, we illustrate this argument in Figure 3. The consumer may check burned calories and enter her meals on a daily level. Also, she may compare her performance to that of her friends and check up on the latest community updates. An app may also remind her of the upcoming workout the next day and suggest a jogging route to ensure that she stays on track to complete a half marathon.

Figure 3: Ongoing Interactions on Relational Digital Platforms

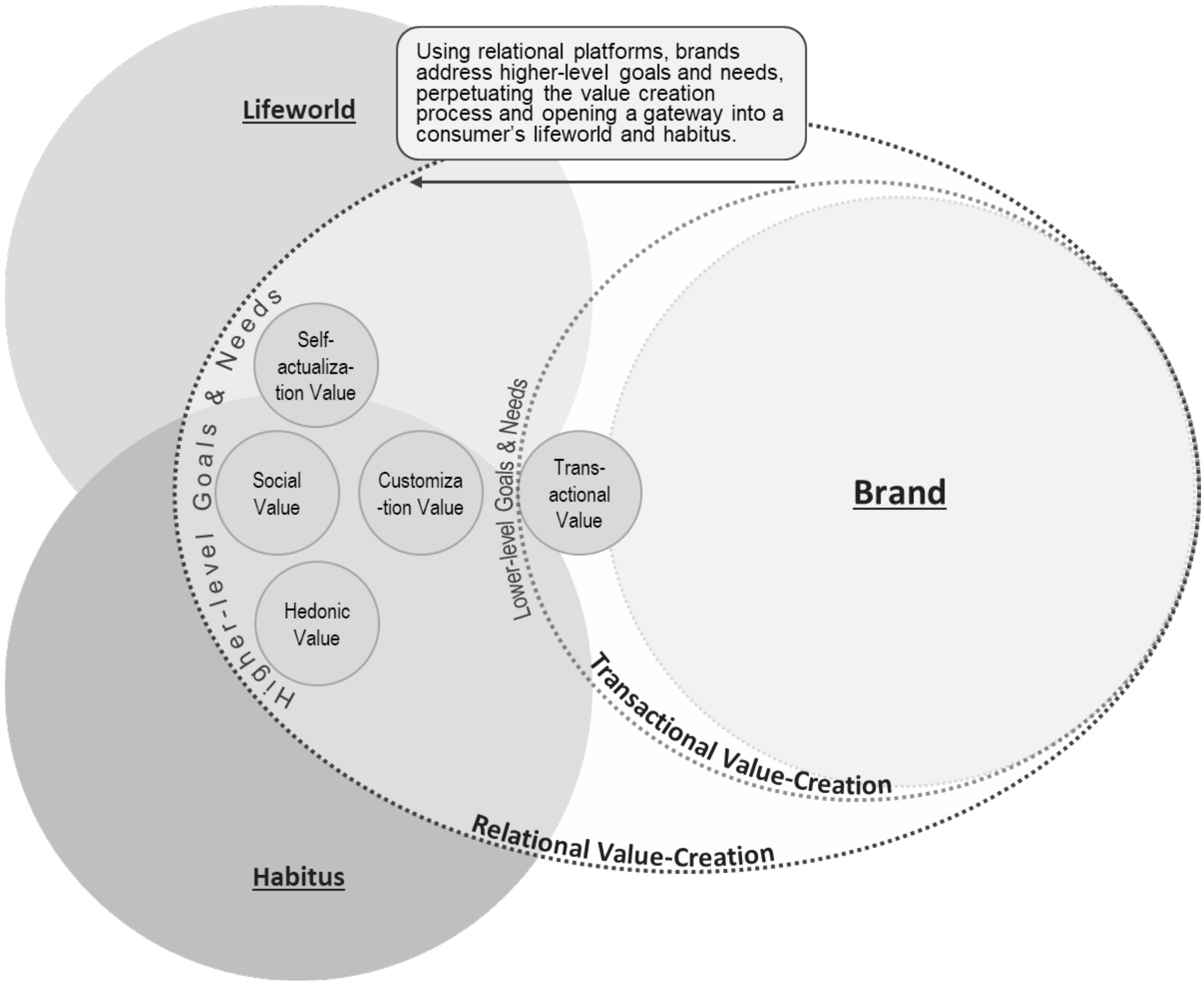


Over time, these interactions not only enter but also *shape* the consumer's lifeworld. The community-initiated interactions constitute social interactions that, as prior research shows, lead to the emergence of unique subcultures within a platform (e.g., Fournier and Lee 2009;

Schau, Muniz, and Arnould 2009). The community's shared culture affects each consumer individually and can carry over to the offline world, for example in the form of product purchases (Manchanda, Packard, and Pattabhiramaiah 2015) or social events (Schau, Muniz, and Arnould 2009). Platform-initiated interactions are increasingly powered by algorithms that are able to provide customized recommendations and content. These algorithms leverage personal data to initiate many value-creating activities that influence a consumer's activities. The platform may prompt her to go for a walk in the park to meet her daily activity goal or to join a running group in the neighborhood. It may suggest a new jogging route or recommend nutritional supplements based on her individual workout patterns. Hence, all these interactions become part of the idiosyncratic set of experiences that form the consumer's lifeworld and by extension build "uniquely into her biography and habitus" (Atkinson 2010, p. 9).

The *habitus* is another prominent sociological concept that becomes important in the context of RDPs. Habitus describes a person's "dispositions, propensities, and schemes of perception and appreciation" (Atkinson 2010, p. 3) that result from past experiences and, importantly, guide her conscious and subconscious actions (Atkinson 2010; Sayer 2005; Bourdieu 1977). An individual's habitus is constantly updated through new experiences and interactions with the lifeworld (Atkinson 2010; Bourdieu 1990). Habitus and lifeworld influence each other reciprocally: The experiences that make up our lifeworld influence our habitus, which guides our actions and decisions. These in turn influence which objects and persons we encounter and interact with, thus shaping which experiences become part of our lifeworld (Atkinson 2010). A relational platform that is now able to enter a consumer's lifeworld by definition also influences her habits and, consequently, her actions. Thus, RDPs can create a considerably more profound brand-consumer relationship in which the brand and its platform guide consumers' daily lives. However, consumers only allow this to happen if the platform creates value for them, specifically in terms of the value components discussed before. We depict this concept in Figure 4.

Figure 4: How Platforms Enter Consumers' Lifeworld and Habitus



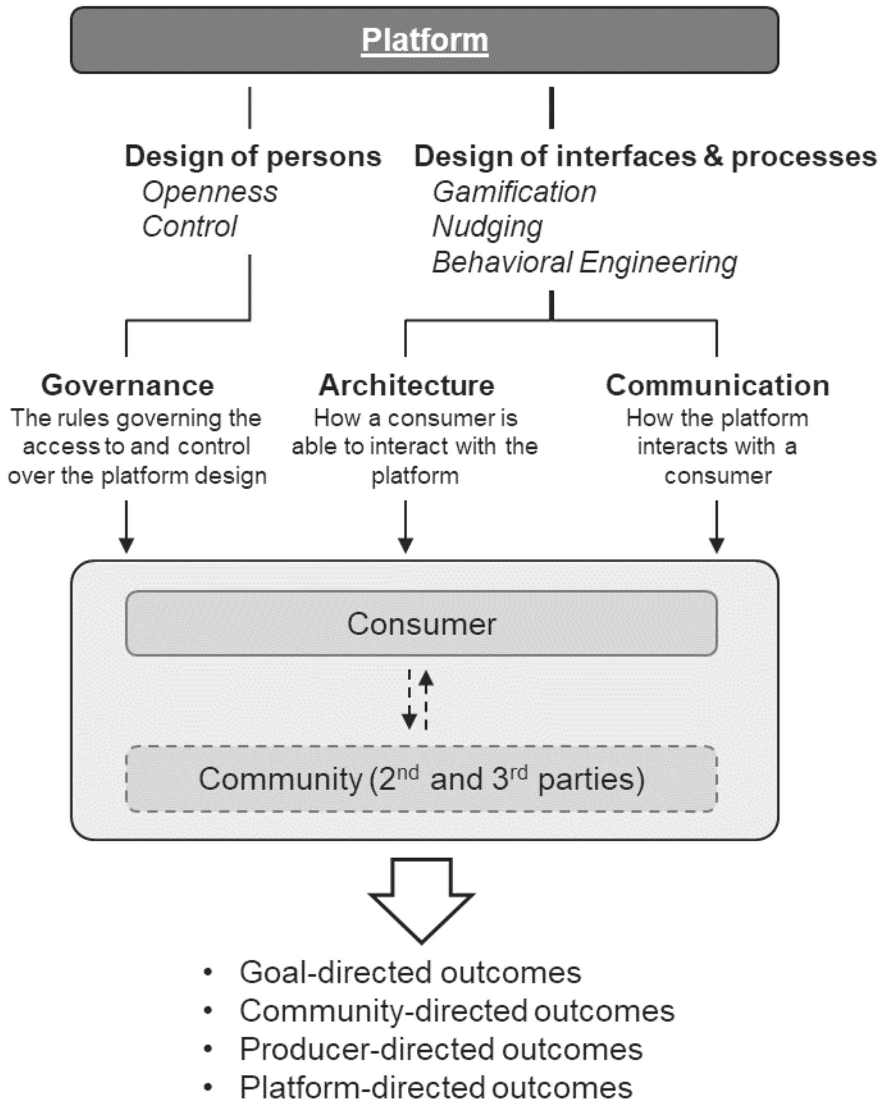
The formation and continuation of this close brand-consumer relationship hinges on providing valuable interactions at all times. Getting this right, however, is not always straightforward.

Platform-initiated interactions and personalization of interfaces can easily be perceived as annoying and intrusive, leading to privacy concerns (Claussen, Kretschmer, and Mayrhofer 2013; Wottrich, Reijmersdal, and Smit 2018). In order to alleviate these consumer concerns, trust has consistently been shown to be an important factor in various settings (Acquisti, Brandimarte, and Loewenstein 2015; Chen and Wang 2019; Sundararajan 2019). Especially in the context of RDPs, trust is a pivotal asset because consumers do not only trust brands with a vast amount of personal data but even grant them access to their lifeworld. The Cambridge Analytical scandal presents a cautionary tale: Facebook gave third parties access to highly sensitive user data, which caused severe pushback from users, sending its stock price down by $120 billion (Frenkel 2018). Hence, building and maintaining consumers' trust is of utmost importance for brands that employ RDPs. Besides privacy concerns, however, platform interactions may lead to further unintended consequences. The machine learning algorithms that power personalization can incorporate biases that lead to discrimination based on gender (Lambrecht and Tucker 2019) and race (Obermeyer et al. 2019). In addition, the platform community may show anti-social and potentially discriminatory behaviors (Edelman, Luca, and Svirsky 2017). Therefore, brands need to monitor outcomes and ensure their fairness.

6 Platform Design Choices

The platform provider acts as a mediator of the interactions on its RDP by controlling the platform's artifacts, processes, persons, and interfaces. Thereby, it—intentionally or unintentionally—influences when, how and what kind of interactions end up on the consumer's interface as well as which information is transmitted to the platform and the community. Platform design decisions can help steer these outcomes. For example, the platform provider controls the content each consumer sees through its approach to content curation (Lazer 2015). It also influences the behavior highlighted and appreciated on the platform through rewards (whether with actual monetary or just virtual incentives). The platform architecture also dictates which consumers interact and how they interact (Spagnoletti, Resca and Lee 2015; Boon, Pitt and Salehi-Sangari 2015); Twitter, for example, limits the number of characters a user can post whereas the communication on Instagram strongly centers on posting and reacting to visual content. Hence, contrary to early platform types such as brand communities, which were mostly self-governed, today's platform providers are much more involved. They purposefully design interactions and components to influence outcomes in terms of individual consumer behavior and the shared culture evolving in the community.

Figure 5: Platform Design Mechanisms



The sociological literature calls the deliberate influence of a governing institution on a person's lifeworld the "colonization" of said lifeworld (Habermas 1987). While in sociology these are typically governments, in our context the platform provider acts as the colonizer of consumers' lifeworlds. As Habermas (1987) argues, colonization is realized through institutions, bureaucratic processes, and market forces based on a monetary regime. On RDPs, monetary rewards can also be at play but may extend to social currency in the form of status and esteem, for example through public recognition of performance (Hamari and Koivisto 2015) or virtual status symbols (Sailer et al. 2017). Additionally, the platform provider can establish institutions and bureaucracy that colonize consumers' lifeworlds through the interfaces and processes that it controls and through which it governs interactions. Consequently, the question arises how to design these components deliberately to elicit desired attitudinal and behavioral outcomes. While this question is also relevant in the context of TDPs and has spurred initial research (e.g., Broekhuizen et al. 2019), we show that the long-term focus of RDPs presents a unique setting. Based on a review of various literature streams (marketing, behavioral economics, information systems, management strategy), we propose several important design mechanisms for RDPs, which we depict in Figure 5 and discuss in the following paragraphs.

6.1 Gamification

The marketing literature shows that companies can employ gamification elements to elicit desired consumer behaviors and attitudes, such as commitment, referrals (Wolf, Weiger and Hammerschmidt 2019), motivation and performance (Groening and Binnewies 2019; Mitchell, Schuster and Jin 2018) as well as innovation adoption (Müller-Stewens et al. 2017). Gamification can be employed in many ways: A platform may use scores, levels, badges, leaderboards, virtual currency and rewards, competitions, games and game-like experiences (Koivisto and Hamari 2019; Sailer et al. 2017). For example, the popular running app *zombie run* implements an interval running exercise into an AR game, in which virtual zombies chase the runner in a post-apocalyptic world. Prior literature shows that consumers are driven to engage in gamified experiences due to both intrinsic motivators, such as self-development and expressive freedom, and extrinsic motivators (e.g., social connectedness and comparison) like leaderboards, badges, or competitions (Mitchell, Schuster and Jin 2018; Wolf, Weiger and Hammerschmidt 2019). Hence, depending on the design, a platform's gamification elements either can act directly on the consumer or indirectly through the social effects elicited by the community members.

Given the possibilities of self-quantification and social comparison paired with the potential of digital enhancements through audio, video, vibration, AR and VR, gamification is an important tool for RDPs to keep consumers engaged and focused on their goal progression. Additionally, the platform provider can use gamification elements to reward user behavior. For example, the platform may award a badge for consumers that have connected with at least 100 people, and thereby reinforce the community aspect of the platform. The platform provider can leverage gamification in its communication with consumers by highlighting earned badges on the interface and implement gamification in its architecture by permitting consumers to challenge and compete with peers. UnderArmour takes an interesting approach to gamification in that they allow third parties to create branded challenges that consumers can participate in.

6.2 Nudging

Gamification and nudging overlap, because gamification elements like badges and digital rewards can nudge consumer behavior, operating through some of the same psychological mechanisms (Bhargava and Loewenstein 2015; Madrian 2014). However, nudging is far broader in its possible application, while lacking the profound experiential and hedonic component of many gamified experiences. As Thaler and Sunstein (2008, p. 6) put it, "a nudge [...] is any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives." Hence, nudging can manifest in many mechanisms well known to marketers such as framing and anchoring, default options, choice architecture, and information presentation (Johnson et al. 2012; Thaler and Sunstein 2008).

While nudging has been researched in a variety of contexts (e.g., Adjerid, Acquisti and Loewenstein 2018; Ungemach et al 2017) and can be important for one-off consumer interactions, it is especially important for RDPs. First, the number and variety of interactions on RDPs are large. Each of these interactions needs to be designed and integrated carefully to achieve the desired outcome. Furthermore, RDPs can easily capture large amounts of data and employ A/B-testing in order to scrutinize the effectiveness of the designs and continuously improve them on an individual level (Wedel and Kannan 2016). This may even culminate in systems that autonomously optimize interface designs for specific outcomes, as has been shown in the context of websites and banner ads (Hauser et al. 2009; Urban et al. 2013).

Second, RDPs continuously interact with consumers over time. Therefore, they may employ nudging methods that leverage past data, such as progress towards a goal, reminders, or informing about consequences of past choices (Sunstein 2014). Additionally, they may nudge choices that are subject to intertemporal biases, like giving in to immediate temptations rather than following previously set goals (Johnson et al. 2012). Many decisions that consumers face imply a series of interconnected choices over time (Gul and Pesendorfer 2001). For example, a consumer who wants to eat out first decides where to eat before selecting an option from the chosen restaurant's menu. How to best nudge these "cascading choices' differs from singular choices, as shown by Adjerid, Acquisti, and Loewenstein (2018) for online privacy choices.

Third, RDPs often allow consumer-to-consumer interactions. Platforms like LinkedIn and Facebook actively suggest new people to connect with, nudging consumers to extend their network and shaping whom they interact with. These platforms also curate the displayed content, hence, influencing whose information users receive. This influence of online social ties may then carry over into the offline world (Lazer 2015; Trepte, Reinecke, and Juechems 2012). The platform provider can also strategically highlight certain behaviors by other members of the community in its communication, and thereby create implicit social norms that nudge consumers to copy that behavior (Sunstein 2014; Hamari and Koivisto 2015).

6.3 Behavioral Engineering

Gamification and nudging are a platform's "soft" levers that subliminally motivate consumers to show specific behaviors while still admitting complete freedom of choice. In contrast, behavioral (economic) engineering focuses on the design of concrete mechanisms that dictate or incentivize a certain course of action (Bolton and Ockenfels 2012). Hence, contrary to nudging and gamification, behavioral engineering is a "hard lever" that does not allow consumers complete freedom and may apply economic incentives, i.e. rewards as well as punishments. These economic incentives are not necessarily monetary but may also be realized through, for instance, a platform's search results ranking (Boon, Pitt and Salehi-Sangari 2015). Prior research shows that setting up a double-blind feedback process prompts users to give more reliable and useful reviews (Bolton, Greiner, and Ockenfels 2013; Fradkin, Grewal, and Holtz 2018). The car-sharing platform ShareNow employs behavioral engineering by rewarding consumers that refuel a car with free credits for future rides. Thingiverse, the platform of 3D printer manufacturer MakerBot, allows users publishing 3D designs to receive a share of revenues for each print, which incentivizes high-quality and useful designs.

6.4 Openness and Control

Platforms can also shape the community of producers and consumers through another hard lever in the form of explicit rules and restrictions. Two fundamental factors are the platform's openness, that is, who is allowed access to the platform, and the degree of control granted to platform participants (Boudreau 2010; Parker and Van Alstyne 2018). Both aspects are among the most complex and crucial design decisions a platform provider needs to make because they affect the co-creation and appropriation of value by consumers and third parties, as well as lock-in and network effects (Parker and van Alstyne 2018; West 2003).

A platform provider may choose between opening the platform to customers only, to a specific subset of customers, or to all consumers, granting them different levels of control.

Likewise, the platform may be closed for third parties, open to a selection of third parties (e.g., only those who offer complementary services), or all third parties (Broekhuizen et al. 2019). The levels of control granted to platform producers and consumers range from allowing interactions with other members, over access to resources and data as well as the customization of interfaces and processes, to providing options for different revenue models (Broekhuizen et al. 2019). The levels of openness and control can be dialed in on a spectrum and calibrated over time. Their effects are not always straightforward (Parker and Van Alstyne 2018): Greater openness and control enable and elevate many of the value components discussed in the first part of this paper, such as assortment and information value as well as all of the relational value components. However, it may also lead to adverse effects such as the reduction in quality of offerings (Broekhuizen et al. 2019) and an increasing fragmentation (Boudreau 2010).

The platform provider can employ the presented hard and soft levers to lead consumers towards desired outcomes. These outcomes may come in different shapes: Some may create value for (1) the platform provider (e.g., a more positive brand perception, increased usage of the platform, more comprehensive data collection), (2) the platform producers (e.g., purchase of a service), (3) the community (e.g., a helpful review), or (4) the individual consumer and her specific goal achievement (e.g., improving her running performance). Importantly, several parties may profit directly or indirectly from the same outcomes. For example, a helpful review not only creates value for the community but indirectly also for the platform provider through elevation of the platform's attractiveness.

Designing a relational platform to elicit self-serving outcomes, however, is not without controversy. Especially the more subversive mechanism like gamification and nudging can be perceived as manipulative and stress-inducing (Mitchell, Schuster, and Jin 2018; Wilkinson 2013). Thorpe and Roper (2019) question whether gamification elements are ethical because they are designed to be highly engaging ("hyper-engaging") and attention-grabbing, encouraging ongoing use and, thus, are extraordinarily effective in inducing behavior change in consumers on a subconscious level. This argument is also reflected in the current debate about certain game mechanics resembling gambling and, therefore, needing to be regulated (Bailey 2018). Similarly, some applied nudging methods border on manipulation and accordingly are called “dark patterns” in the industry (Brignull 2019). For example, Amazon hides the option to close ones’ account deep in its settings. LinkedIn repeatedly prompts users to invite their entire address book to the platform, preselecting and visually highlighting the option through which users give consent (Brignull 2019). Further, badly designed gamification elements have been shown to lead to reduced motivation, lack of autonomy, and plunging performance (Hanus and Fox 2015; Groening and Binnewies 2019; Mitchell, Schuster, and Jin 2018). Ill-conceived mechanisms thus bear the risk of provoking adverse effects for consumers and society. We outline these along with possible remedies subsequently.

7 Implications

Platforms are not all created equal. On the contrary, industry practice and academia have given rise to a plethora of platform types and terminologies. This paper developed a classification of the platform universe along the two dimensions of transactional and relational value creation and characterized the major concepts discussed in the literature. Furthermore, we identified a set of distinct values stressed by each dimension to show why consumers adopt and use different platform types. We then turned to the sociological implications of current developments in relational platform architectures. We argue that RDPs have the potential to transcend previous boundaries of relationship marketing, which typically separated the two worlds of brands and consumers by catering to consumers’ higher-level goals and blending with their lifeworlds and habitus. We propose that platforms are thus developing into a Trojan horse to colonize (Habermas 1987) the everyday actions and attitudes of consumers and present several mechanisms platform providers apply to elicit such outcomes.

7.1 Implications for Platform Brands

Although we are expecting to see the emergence of more platforms with both high relational and transactional value in the near future, they are likely to coexist alongside the many platform types that occupy the different quadrants of our 2x2 matrix. Not every platform needs to do everything. Instead, the two dimensions and underlying value components can guide brands to ensure their platform "hits their intended sweet spot" and aligns with their marketing strategy. The classification assists managers in grasping the platform universe, setting suitable goals for their initiative, and taking appropriate action to achieve these goals. Depending on the share of transactional and relational elements, brands need to enhance and communicate the values that create competitive advantage on the respective playing field.

In particular, if the platform focuses on facilitating transactions, then the brand should intensify efforts to acquire third-party suppliers to broaden the assortment, refine algorithms and filters to optimize matchmaking outcomes, and implement a quality management system to ensure fulfillment standards. In doing so, these platforms need to account for the inherent hierarchy of value components, with assortment value as the sine-qua-non for all subsequent activities. That is, without a large assortment, benefits of finding matches, providing suitable information, and guaranteeing common fulfillment standards remain limited. As the assortment grows brands need to provide all value components simultaneously. Otherwise, they risk that consumers do not find what they are looking for and their platform experience suffers.

Priorities for RDPs differ substantially. Here, value components are not as co-dependent but address heterogeneous consumer needs. Some place high value on social interaction, others on hedonic elements, and again others on the possibility to customize. However, self-actualization constitutes the pinnacle of relational value creation and managers who want to build profound and perpetuated consumer relationships should seek to deliver on this front.

Even simple features, such as an automobile platform giving feedback on how to adjust once driving to be more ecological, can contribute to self-actualization value.

Furthermore, perpetual value creation is key to achieve customer lock-in. Attention is limited and rival offerings are ubiquitous. To really become part of a person's lifeworld and habitus, the platform must make itself indispensable. Brands can get there, for example, by occupying important, higher-level goal categories (e.g., fitness, lifestyle, food, DIY, pets, home, finances, etc.) and covering the entire range of activities, information, recommendations, products, and services related to these goals. Qualitative consumer research may help brands assess consumers' higher-level goals. The point is that value creation must be holistic to blend with consumers' lifeworlds. Limited applications that focus on a specific task might create repeat usage, but the corresponding brand remains in its own space, accessed from time to time by the user. At this level of integration, a seamless connection between the two will never be possible.

Once an RDP has entered a consumer's lifeworld and habitus, the platform design elements depicted in the previous chapter can help optimize outcomes. For maximum impact, we propose to integrate elements of all four mechanisms while carefully balancing soft (gamification and nudging) and hard (behavioral engineering, openness, and control) levers so that consumers do not feel restricted or niggled but are not tempted to exploit any loopholes, either.

To achieve this, platforms with predominantly relational benefits need to build new competencies. These are, on the one hand, technical in nature: Providers need to be able to build a system that can handle the complexities of a platform architecture owing to the variety of interfaces, data sources, participants, and devices. Additionally, data management and analysis skills are crucial in leveraging machine learning to initiate automated value-creating interactions with consumers. On the other hand, the farther brands try to advance into consumers' lifeworlds, the more delicately interactions should be *orchestrated*. This is because relationships can go south very quickly if consumers feel censored, manipulated, or patronized. Moreover, as shown in the previous chapters, platform mechanisms can easily lead to unintended and even discriminatory outcomes. Therefore, brands need to monitor the platform outcomes continuously from both, quantitative as well as qualitative, perspectives.

The integration of platforms into consumers' lifeworlds and habitus gives brands tremendous (and sometimes terrifying) power over information flows and decision making. On RDPs, they can colonize many different aspects of everyday life such as sports, nutrition, lifestyle, social connections, products, and services so that consumers no longer notice let alone scrutinize the nature and source of information. The brand's world becomes their own world. Therefore, it is crucial for brands to set up a team occupied with the behavioral and sociological implications of the platform architecture. It should include specialists from psychology, sociology, behavioral sciences, and marketing to ensure that platform features are socially and ethically acceptable and in line with the company's core values. Not every feature that is technically feasible and potentially even profitable should be implemented. Thus, in an increasingly technology-dominated playing field CMOs continue to play a crucial role.

Given the lack of platforms high on transactional *and* relational value, brands may be tempted to launch this type of platform first. Indeed, this could be a game-changer because such platforms would provide a very broad and deep offering, making it a very versatile interface. However, we caution brands aiming to walk this path because combining highly relational and transactional aspects could be risky. Imagine Adidas pushing large-scale product recommendations on their Runtastic platform or Google using health data from the recently acquired Fitbit to feed its ad network. There is a good chance that these self-serving actions will provoke pushback. Therefore, we suggest to go at it gradually and iteratively to not overstep any boundaries. Commercializing too fast and too boldly, especially exploiting cross- and up-selling opportunities, alienates consumers. Offering competitor products alongside own products, however, may signal that the platform has indeed consumers' best interests at heart.

7.2 Implications for Consumers, Regulatory Entities, and Society

In light of the ever-deeper penetration of platforms into the consumers' lifeworlds, the most pressing question is: How much power should we grant platform brands to accumulate and exercise? This is an individual as well as a societal question. Apart from the brands' voluntary commitment to adhere to ethical standards, we stress the necessity to educate consumers and regulate where undesirable social outcomes emerge. This is because platform prevalence bears the risk of loss of privacy, restriction of the freedom of choice, loss of independence, and violation of equality, among others (Wertenbroch 2019; Kramer et al. 2014). Precedents exist in social media: For instance, Bakshy, Messing, and Adamic (2015) show that personalization of content leads to filter bubbles, where individuals increasingly receive information that matches their own attitudes and behaviors. Recently, the American government sued Facebook because its algorithm discriminated by race and gender when showing ads for housing—a violation of the Fair Housing Act (The Economist 2019). The threat of platform environments exerting monopoly power over consumers' content consumption, information search, and shopping habits need to be closely monitored. Consumers, regulatory entities, and society should set boundaries depending on how much control they want to give up. The tradeoff is between relevance and convenience on the one hand, and intrusiveness and lack of freedom on the other hand.

The more deeply brands enter consumers' lifeworld and habitus, the more personal data they are able to gather. It is therefore also important to determine which data points platform providers can use for which purposes. For example, firms may use data on consumers' eating and exercising habits to evaluate individual insurance risks. This, however, not only violates the democratic principle of equality (Wertenbroch 2019) but also leads the insurance concept ad absurdum, as risks are no longer pooled. The result would be that everybody effectively pays their own medical bills, which undermines the idea of most healthcare systems.

Furthermore, the depicted behavioral design elements may prompt consumers to perform potentially harmful actions they would otherwise not engage in. For example, the social e-commerce shop Pinduoduo gave users discounts on products for sharing content with their friends on WeChat, effectively buying word-of-mouth. Athey, Catalini, and Tucker (2017) show that consumers can be easily incentivized to not only to give up their own private data but also that of their friends. Obviously, a dark side to nudging, gamification, and behavioral engineering exists that can be misused especially in complex multiparty systems. Incentivizing people to consume and spread content, disclose private data, or recommend products may have severely detrimental effects on the individual and society. Government and not-for-profit entities should challenge platform innovations regularly and prosecute any abuses. It is also important to establish faster legislative processes to take timely countermeasures if platform designs have unintended consequences.

Despite these justified points of caution, platforms have an immense potential for creating value for consumers. Since platforms involve a variety of third-party suppliers controlling their own content and activities, pluralism is part of their DNA. Consumers act as co-creators of products, content, and services that otherwise would not exist at all or only at high costs. In this way, platforms are able to serve niche consumers and fringe groups usually underserved in the traditional marketplace. As many functionalities on RDPs are paid with data instead of cash, even low-income consumers can enjoy high-quality services, effectively counteracting many societies' widening poverty gap. Moreover, TDPs and RDPs present consumers and businesses with additional sources of income. Furthermore, through smart design choices, deeply embedded platforms can change human behavior for the better, making us healthier, more balanced, knowledgeable, and connected. As much as skepticism is warranted, it is important to impose regulations using sound judgment to not curtail the many advantages these new technologies bring about.

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ESSAY III: SKIPPABLE AND NON-SKIPPABLE ADS – THE YIN AND YANG OF ONLINE VIDEO ADVERTISING

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ABSTRACT

Skippable online video advertisements have been around for almost ten years (Pashkevich et al. 2012) and are widely adopted by marketers (IAB Europe 2018). Nonetheless, literature on this unique ad format is scarce and lacks a detailed understanding of how it is perceived by consumers. Especially engaging in skipping poses an interesting conundrum that lacks research: On the one hand, the consumer can avoid the ad, which usually are perceived as annoying, but on the other hand, her ad viewing experience and the ad's narrative are disrupted. This study sheds light on this issue and analyses how skippability and skipping influence consumers' attitudes towards the ad and the brand. My results show that although skipping is self-imposed, it causes users to enjoy the ad less and creates a feeling of irritation. I present and test strategies for advertisers that help mitigate this effect. In particular, I show that displaying the brand and product during the initial seconds of a skippable ad leads to significantly better ad and brand perceptions. Also, combining skippable with non-skippable ad formats in a campaign significantly improves the performance vis-à-vis ad campaigns that only feature skippable ads.

Keywords: Online video advertising, skippable ads, advertising avoidance

1 Introduction

In 2019, for the first time in history, digital advertising spending has surpassed spending in offline channels (Enberg 2019). An important driver of this growth has been online video advertising (OVA) for which expenditures increased by 20% from 2017 to 2018 to a total of $32 billion globally, which accounts for a fourth of total spending on online advertising and is forecasted to increase to a third by 2021 (Statista 2019). Online video ads offer new and unique opportunities for marketers. Besides the possibility of personalization, targeting and retargeting that it shares with other digital advertising methods (Bleier and Eisenbeiss 2015), a novel ad format that is specific to OVA has evolved: skippable ads. When a consumer encounters a skippable ad, she can skip it by the press of a button but only after she has watched the ad for a minimum required time, usually five seconds (Pashkevich et al. 2012). OVA is thus the only ad format in which the advertiser can actively grant consumers the option to avoid the ad. However, it does require consumers to watch at least a fraction of the ad so that ad avoidance through skipping is distinctly different from other types of ad avoidance such as zapping (i.e. switching the TV channel) or the usage of ad-blocking software, which both cause consumers to avoid entire ads altogether (Campbell et al. 2017; Dukes, Liu, and Shuai 2019). Despite its unique characteristics, advertising avoidance by skipping is scarcely researched so that it remains unclear how skipping affects consumers' ad experience and brand perceptions.

Skippable ads are adopted widely by marketers with 80% of them reporting to be using this format (IAB Europe 2018). In addition, skippable ads are already finding their way onto consumers' TVs, for example through YouTube's apps on smart TVs (Google 2019). Hence, given their novelty and growing relevance, properly understanding skippable ads, how they are perceived by consumers as well as how they affect marketing outcomes is crucial for managers and academics alike.

When consumers encounter skippable ads, multiple, partly opposing effects operate simultaneously. Most researchers argue that skippable ads decrease the intrusiveness and irritation consumers perceive when watching ads because they can easily skip the ad if they dislike it (Campbell et al. 2017; Jeon et al. 2019; Pashkevich et al. 2012). At the same time, however, I argue based on transportation theory (Green and Brock 2000) that skipping and thus only watching a fraction of a video ad considerably disrupts consumers' ad experience leading to a significantly worse perception and enjoyment of the ad. This, in turn, may adversely affect brand attitudes, as shown in prior research in the context of zipping, i.e. fast-forwarding through an ad in prerecorded TV content (Stout and Burda 1989). Prior studies find that 65-70% of all skippable video ads are skipped and only 25% of consumers end up watching more than ten seconds of the ad (Arantes, Figueiredo, and Almeida 2016; MAGNA 2017). Therefore, it is crucial for marketers to understand how this widely spread skipping behavior and the associated partial ad exposure affect consumers' ad and brand perceptions and how to optimally design and implement OVA formats in their campaigns.

There are only few studies to data that have analyzed skippable ads. The majority of them focuses on the antecedents of skipping (e.g. Belanche, Flavián, and Pérez-Rueda 2017a, 2017b; Campbell et al. 2017; Jeon et al. 2019), while a detailed understanding of the process underlying perceptions of skippable and skipped ads and their behavioral and attitudinal consequences is still lacking. To address this gap in the literature and to provide managers with actionable insights on how to best utilize OVA, I answer the following research questions:

1) How do skippable ads influence consumers' ad and brand perceptions and what part does the initial, non-skippable part of the ad play?
2) How does skipping influence consumers' perception of an ad?
3) How should skippable ads be designed and implemented into OVA campaigns to optimize consumers' ad and brand perceptions?

I analyze these research questions by means of three laboratory studies that replicate a typical online content viewing experience. The design allows me to tightly control for confounding factors and to administer comprehensive questionnaires to uncover the processes underlying consumers' perception of skippable ads.

In doing so, I make several contributions. *First*, I describe in detail how consumers perceive skippable ads, being the first to uncover the underlying opposing effects. I find that skippable ads indeed can lead to a reduction in perceived intrusiveness and irritation improving ad and brand attitudes. However, I also find that skipping significantly worsens consumers' enjoyment of the ad, thus increasing irritation and lowering its persuasive power.

Second, I show that the initial, non-skippable part of a skippable ad plays a crucial role in its effectiveness and that while non-skippable ads should rely on a strong non-commercial narrative focus, skippable ads need to take a commercial focus, highlight the brand and advertised product during its initial seconds. In this way, advertisers are able to mitigate the above mentioned negative effects of skipping on ad enjoyment.

Third, studies to date have consistently looked at skippable and non-skippable ads as substitutes and indeed so far no major advertising network offers campaign setups that combine both formats. However, my results show that skippable and non-skippable ads should be seen as complements that each address the other format's weaknesses. Specifically, I show that forcing full ad exposure during the first ad encounter and making subsequent ad encounters skippable leads to optimal brand outcomes and is also perceived most favorably by consumers.

In the following section, I first provide an overview of the literature on ad avoidance and skippable ads before introducing the underlying theories and developing the conceptual framework. Subsequently, I present and discuss the results of each of the three studies and conclude with a general discussion of my findings as well as concrete implications for management and future research.

2 Skippable Ads and Advertising Avoidance

Consumers always had an ambivalent relationship with advertising: On the one hand, they perceive ads as a nuisance (Johnson 2013; Olney, Holbrook and Batra 1991; Wilbur 2008) keeping them from consuming the content they desire (Dukes and Gal-Or 2003; Ha 1996). Therefore, consumers perceive ads as a restriction of their freedom (Edwards, Li, and Lee 2002), which evokes reactance, i.e. the urge to restore that freedom (Brehm and Brehm 1981). This can lead to advertising avoidance (Bhattacharjee 2010; Edwards, Li, and Lee 2002; Morimoto and Chang 2009). Prior research shows that the more intrusive and irritating an ad is perceived, the higher the reactance and, thus, the degree of advertising avoidance (Edwards, Li, and Lee 2002; Li, Edwards, and Lee 2002; Olney, Holbrook, and Batra 1991). The desire to avoid ads has even led to the development of a sizeable industry offering software and apps that suppress online ads (Shiller, Waldfogel, and Ryan 2018).

On the other hand, advertisers take great effort to craft ads that not only inform but also entertain consumers (Weinberger and Gulas 1992; Ducoffe 1995, 1996). At its extreme, ads can generate substantial hype such as, for example, ads during the super bowl (Siefert et al. 2009) or viral ads that are shared frenetically among consumers (Teixeira 2012; Tellis et al. 2019). Prior research shows that enjoyable ads reduce advertising avoidance (Campbell et al. 2017; Siddarth and Chattopadhyay 1998; Elpers, Wedel, and Pieters 2003) by reducing perceived intrusiveness and irritation (Edwards, Li, and Lee 2002). Nonetheless, consumers tend to disregard and underestimate the gratification they receive from watching ads while overestimating their negative effects (Nelson, Meyvis, and Gallak 2009; Yang and Smith 2009) and, thus, end up avoiding ads they may have derived value from.

Advertising avoidance boils down to two methods: cognitive avoidance by directing one’s attention away from the ad, and behavioral/mechanical avoidance, for example, by leaving the room or switching the TV channel (Speck and Elliott 1997). While cognitive avoidance can be applied to any advertising method, behavioral/mechanical avoidance is highly dependent on the advertising medium: When watching TV, consumers may engage in zapping or zipping (Cronin and Menelly 1992; Siddarth and Chattopadhyay 1998; Van Meurs 1998) whereas online, consumers can use ad-blocking software (e.g. Shiller, Waldfogel, and Ryan 2018; Redondo and Aznar 2018) or close display banners with a click (e.g. Cho and Cheon 2004; Edwards, Li, and Lee 2002; Drèze and Hussherr 2003).

Ad skipping has introduced a novel form of behavioral/mechanical avoidance of online video advertising. First implemented by YouTube in 2010 (Pashkevich et al. 2012), skippable ads force users to watch a fraction of the ad (usually five seconds) after which they are allowed to skip the ad and view the desired content (Pashkevich et al. 2012). If they do not skip the ad, it keeps playing until the end at which point the website automatically directs users to the requested content. Hence, ad avoidance through skipping possesses unique features distinguishing it from other types of ad avoidance: First, skippable ads require consumers to watch the initial seconds of an ad while other behaviors such as zapping, zipping and ad-blocking eliminate an ad altogether (Dukes, Liu, and Shuai 2019; Elpers, Wedel, and Pieters 2003) or considerably distort the ad viewing experience (Bellman, Schweda, and Varan 2010; Cronin and Menelly 1992). Advertisers can leverage skippable OVA's initial seconds to spark interest in consumers (keeping them from skipping) or to convey the ad message in a way that even consumers who end up skipping have a touchpoint with the brand. Second, while pop-up banner ads work similarly to skippable OVA in the way that consumers are forcefully exposed to the ad before they are able to close it, the crucial difference is that since OVA's content keeps evolving, the consumer might derive additional utility from continuing to watch the ad. Additionally, watching the ad represents the default option for skippable ads because the consumer reaches her desired content even if she does not engage in any action. In contrast, when faced with a pop-up banner ad, users have to actively close it or otherwise, they will not be able to consume the requested content. Third, skippable ads are a form of advertising avoidance consciously enabled by the advertiser because they can typically choose between a skippable and non-skippable ad format when setting up the campaign. Accordingly, this control and empowerment given to the consumer may reflect positively on the brand (Liu and Shrum 2009; Stewart and Pavlou 2002).

3 Literature Review

Academic studies on skippable ads are still limited and mostly focus on the antecedents of skipping behavior. Belanche, Flavian, and Perez-Rueda (2017a, 2017b) find that previous exposure to a skippable ad format, skipping habit, and time urgency lead to increased skipping while arousing and context congruent ads are watched longer. Campell and colleagues (2017) identify a variety of advertising content factors such as humor, entertainment, and attention-grabbing tactics associated with consumers' skipping rates. Jeon and colleagues (2019) analyze how the presence of a timer in skippable and non-skippable ads influences perceived irritation and, in turn, skipping.

While in the TV setting, around 30% of viewers engage in zapping (Schweidel and Kent 2010; Steinberg and Hampp 2007), 65-70% of users skip video ads online of which 75% do not watch more than ten seconds of the ad (Arantes, Figueiredo, and Almeida 2016; MAGNA 2017). As suggested by these numbers and confirmed by surveys, most consumers (76%) skip out of habit rather than because they disliked the ad, the product, or brand (MAGNA 2017). Watching an ad, on the contrary, is primarily driven by users enjoying the creative, a preference for the brand, and the ad being so short that it is not perceived worth the effort of skipping (MAGNA 2017). Hence, although it is often argued that skippable ads encourage self-selection of consumers that are truly interested in the advertised offering (Dukes, Liu, and Shuai 2019; Pashkevich et al. 2012), prior research shows that skipping is mainly driven by pure habit or enjoyment of the ad creative and only to a limited degree by an interest in the brand.

While prior studies make important contributions to understanding advertising avoidance, the underlying premise of optimizing skippable ads for the lowest skipping rate is problematic. After all, solely watching an ad does not imply achieving the intended goal of improved brand awareness, brand image, or sales. On the contrary, consumers may even be annoyed by ads designed to keep them from skipping (Campbell 1995; Darke and Ritchie 2007). Additionally, inconspicuous branding in ads might decrease skipping (Campbell 1995), but might also be detrimental for brand recall and awareness, especially for users that skip. Furthermore, although the majority of skipping occurs out of habit, there is still a significant fraction of users that self-selects by choosing to skip an ad. This prevents the advertiser from spending advertising budget on users without interest in the product category or brand. Hence, purely optimizing ads for minimum skipping rates may imply retaining viewers that otherwise would have opted out of viewing the ad and on whom budget is wasted.

Therefore, the more crucial question and the core of my research is how skippable ads and skipping influence consumers' ad perceptions and brand outcomes, and how they can be leveraged optimally, especially in comparison to non-skippable OVA. Conversations with practitioners reveal an uncertainty concerning the choice between skippable and non-skippable ad formats driven by the inherent conflict between granting consumers control versus communicating the advertising message. Hence, they are unsure which format is more effective and under what circumstances.

Literature to date lacks the necessary insights to solve this conundrum because studies have either ignored the underlying process that explains how consumers perceive these ads (Pashkevich et al. 2012; Campbell et al. 2017) or only analyzed singular components such as intrusiveness and irritation (Belanche, Flavián, and Pérez-Rueda 2017a, 2017b; Jeon et al. 2019). Other findings are contradictory. For example, the analytical model developed by Dukes, Liu, and Suhai (2019) shows that skippable ads may be less effective for advertisers in reaching consumers than traditional non-skippable formats, and Goodrich, Schiller, and Galletta (2015) find longer ads to be perceived more favorably. By contrast, Pashkevich et al. (2012) show that while users that voluntarily watch an ad are more likely to engage with the brand than those who skip, skippable and non-skippable ad formats are, overall, equally effective. Bellman, Schweda, and Varan (2010) experimentally yield the same results using skippable ads in prerecorded TV content.

Hence, my results shed light on this disputed field and thus make several contributions to the literature. I specifically compare skippable to non-skippable OVA in a laboratory setting which allows me to take a detailed look at the underlying process of consumers' perceptions of skippable ads and OVA in general. Thus, I am able to identify the effects of skipping on ad and brand perceptions and show conditions that influence the effectiveness of skippable OVA. Specifically, I focus on the ads commercial focus in the form of brand visibility during the initial, non-skippable part of the ad which proves to be an important moderator of the effectiveness of skippable ads. Additionally, I introduce a new perspective on OVA, being the first to analyze how the skippable and non-skippable formats can be used alongside each other as complements over the course of an ad campaign in order to improve consumers' ad and brand perceptions.

4 Conceptual Background

Consumers' perception of ads can be described by the umbrella construct *irritation*, which is the result of an ad's content (e.g. its entertainment level), execution (e.g. its image quality and length), and placement (e.g. the degree to which the ad keeps the user away from the desired content) (Aaker and Burzzone 1985; Li, Edwards, and Lee 2002). Making a regular OVA skippable, therefore, influences irritation on two levels—the placement and the ad content. While skippable ads initially block the content just as much as non-skippable ads, users can easily discard them once skipping is granted, which may alleviate intrusiveness and irritation caused by the ad. However, as users that skip only watch a fraction of the ad content, they experience a disruption to the narration, which, as transportation theory shows, evokes displeasure and irritation (Green and Brock 2000; Van Laer et al. 2014; Wang and Calder 2006). These are the two fundamental opposing forces that operate alongside each other in skippable ads and for which I explicate the underlying theories in more detail in the following.

4.1 Entertainment and Attitude towards the Ad

The value that an ad provides in terms of information and especially entertainment has consistently been shown to reduce irritation (Edwards, Li, and Lee 2002; Goodrich, Schiller, and Galletta 2015; Ying, Korneliussen, and Gronhaug 2009). In the context of skippable ads, however, the act of skipping leads users to consume less of the ad content which may decrease its entertainment value. Prior research shows that longer ads are generally perceived as more entertaining than shorter ads (Goodrich, Schiller, and Galletta 2015; Newstead and Romaniuk 2009). This is consistent with transportation theory, which argues that all types of content, especially multimedia formats like videos, have the potential to transport consumers, that is captivating them in their narrative (Green and Brock 2000), and bringing them into a state of "flow" (Csikszentmihalyi 1997; Green, Brock, and Kaufman 2004). This transportation generates enjoyment (Green, Brock, and Kaufman 2004; Chang 2009; Van Laer et al. 2014) and causes narrative ads to be highly persuasive and effective in elevating brand attitudes (Escalas 2004a; 2004b; 2006; Brechman and Purvis 2015). Disrupting this state, however, has been shown to induce negative feelings in the viewer (Green, Brock, and Kaufman 2004; Wang and Calder 2006; 2009).

Prior literature usually regards ads as disruptors of a transportation experience that consumers derive from the content they are currently watching (Wang and Calder 2006; 2009), for example TV ads that interrupt a show. By contrast, this study focuses on pre-roll OVAs, i.e. ads that play *before* the requested content starts. Therefore, consumers have not been transported by their requested content, yet, and, accordingly, the ad itself is not disrupting a state of transportation. Additionally, consumers may be more receptive to being transported by the ad than in a typical TV setting, which may further aggravate the negative feelings caused by skipping the ad.

It might seem counterintuitive that a consumer may disrupt her own experience when this disruption would be associated with negative feelings. However, Nelson, Meyvis, and Gallak (2009) and Nelson and Mayvis (2008) show empirically that consumers in many cases fail to realize how their actions end up negatively affecting their hedonic experiences. Specifically, the authors demonstrate that consumers enjoy watching TV more when the content is interrupted by ads which, among other effects, is driven by consumers overestimating their negative perception of ads (Nelson, Meyvis, and Gallak 2009; Yang and Smith 2009).

Hence, in the case of skippable ads, consumers may start to be transported into the narrative of the ad, but through an overestimation of the negative feelings associated with watching the ad, consumers skip the ad and, thereby, disrupt themselves in their ad viewing experience causing displeasure. This may also lead to higher perceived intrusiveness as shown by Edwards, Li, and Lee (2002), who find that more entertaining ads are perceived as less intrusive.

When a user skips the ad, it has less potential to deliver its entertainment, emotions, creativity, and narration which all have been shown to reinforce the delivery of the intended advertising message and the persuasion of consumers (Edell and Burke 1987; Van Laer et al. 2014; Yang and Smith 2009). Therefore, I expect that skippable ads are enjoyed less than non-skippable ads, which adversely affects consumers' perceived irritation and brand attitudes.

Van Laer and colleagues (2014) find that ads with a strong non-commercial focus have a higher potential to transport viewers and elicit positive brand outcomes than highly commercially-oriented ads. This may also help explain why some studies find that consumers perceive longer ads more positively than shorter ones (Goodrich, Schiller, and Galletta 2015; Newstead and Romaniuk 2009): Not only do longer ads have more time to tell a story that transports the viewer, but their advertising message is less obvious and takes up a smaller fraction of the ad, hiding the ad's commercial focus and thus further elevating transportation of viewers. For skippable ads, this means that contrary to non-skippable ads, a strong narrative, non-commercial focus, especially in the initial, non-skippable five seconds of the ad is disadvantageous because it increases transportation, which in turn aggravates the negative feelings caused by disrupting this state through skipping. Therefore, I expect that skippable ads with a high commercial focus are perceived as less irritating and lead to better brand perceptions than skippable ads with low commercial focus, whereas for non-skippable ads, the effects are reversed.

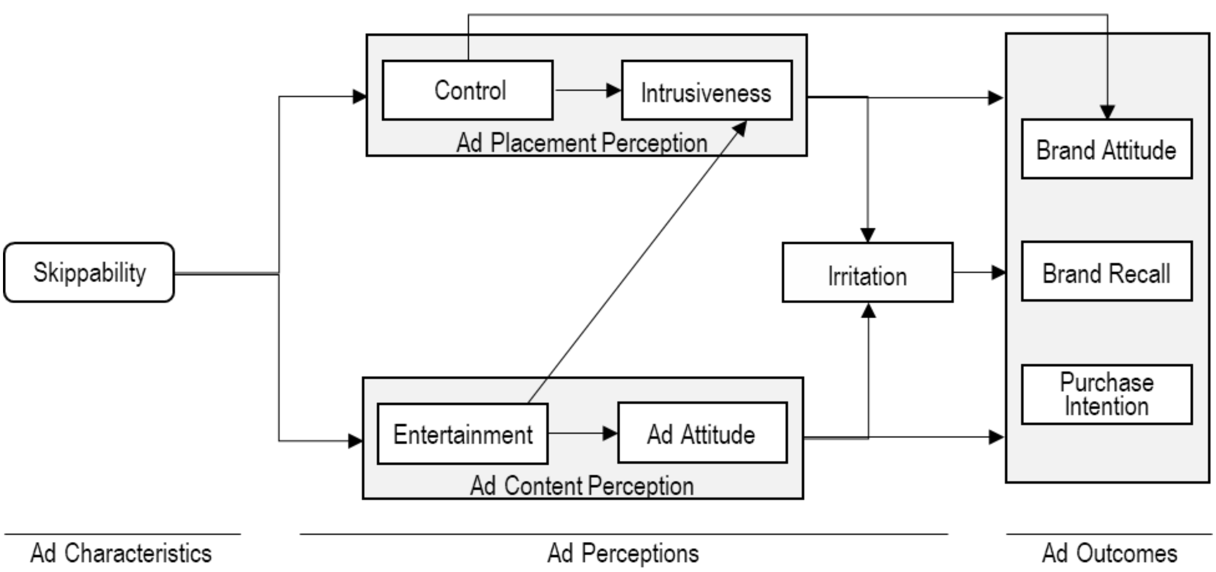
4.2 Intrusiveness and Control

Advertising exposures—whether in the form of TV, pop-up banners, or video ads—keep users away from the content they desire which leads to feelings of intrusiveness (Campbell et al. 2017; Edwards, Li, and Lee 2002; McCoy et al. 2008). Intrusiveness relates to the degree to which a user perceives the ad as an obstruction to her intended content consumption (Ha 1996; Li, Edwards, and Lee 2002). Hence, skippable ads are commonly expected to decrease intrusiveness because by providing consumers the option to skip the ad, irrespective of whether they exercise this option, the perception of the ad as an impediment should decrease because consumers can easily remove it and continue to the requested content (Jeon et al. 2019; Pashkevich et al. 2012). Additionally, when consumers skip, the length of interruption is reduced, which also decreases the obstruction and perceived intrusiveness (Hegner, Kusse, and Pruyn 2016).

A lower level of intrusiveness and the associated decrease in irritation have been shown to elevate brand attitudes and purchase intentions (Aaker and Bruzzone 1985; Goodrich, Schiller, and Galletta 2015; MacKenzie and Lutz 1989). However, past research also shows that intrusive ads may increase brand attitudes and recall if they are able to communicate the advertising message (Bell and Buchner 2017; Cho, Lee, and Tharp 2001; Goldfarb and Tucker 2011). Hence, the low intrusiveness of skippable ads may deteriorate brand outcomes when paired with a low commercial focus of the ad. Therefore, I expect skippable ads to improve consumers' perceived intrusiveness and brand outcomes. However, brand outcomes will also depend on the commercial focus of the skippable ad with a low commercial focus leading to worse brand outcomes than a high commercial focus.

The option to skip also generates a perception of control over and interactivity with the advertising experience (Jeon et al. 2019), which has been shown to improve the ad and brand perceptions (Acar and Puntoni 2016; Liu and Shrum 2009; McCoy et al. 2008; Stewart and Pavlou 2002). Therefore, I expect perceived control to decrease intrusiveness and irritation, improving consumers' brand perceptions as well as exercising a direct positive effect on consumers' brand perceptions.

Figure 1: Conceptual Framework



I summarize the proposed effects derived from literature in the conceptual framework depicted in Figure 1. The upper part represents the potential advantages of skippable ads that reduce irritation and improve brand outcomes whereas the lower part shows potential disadvantages causing higher irritation and worse brand outcomes.

4.3 Optimizing Skippable Ads

Multiple strategies may exist to optimize the effectiveness of skippable ads. I focus on two that are highly specific to the ad format: taking advantage of the initial, non-skippable seconds of the ad and combining skippable with non-skippable ad formats.

Leveraging the first five seconds. Given that consumers need to watch the initial five seconds of a skippable ad, the question of how to optimally design this section to optimize brand outcomes arises. Compared to non-skippable ads, the optimal design may differ significantly. My conversations with practitioners as well as observations of skippable OVA in the field suggest two contrasting strategies: Either, hiding the ad's commercial focus revealing the brand and ad message only at the end of the ad and instead stressing its narrative aspects in order to keep consumers from skipping the ad, or highlighting the brand and product early in the ad to create brand awareness even among consumers that skip the ad.

The previous discussion shows that a) transportation through a strong narrative, non-commercial focus may be counterproductive for skippable ads because skipping disrupts the transportation experience and elicits irritation (Van Laer et al. 2014), and b) a low commercial focus paired with skippable ads' low intrusiveness may negatively affect brand outcomes (Bell and Buchner 2017; Cho, Lee, and Tharp 2001; Goldfarb and Tucker 2011). Therefore, I expect that the strategy to use high brand visibility during the initial five seconds of the ad leads to better brand outcomes than the strategy of using low brand visibility.

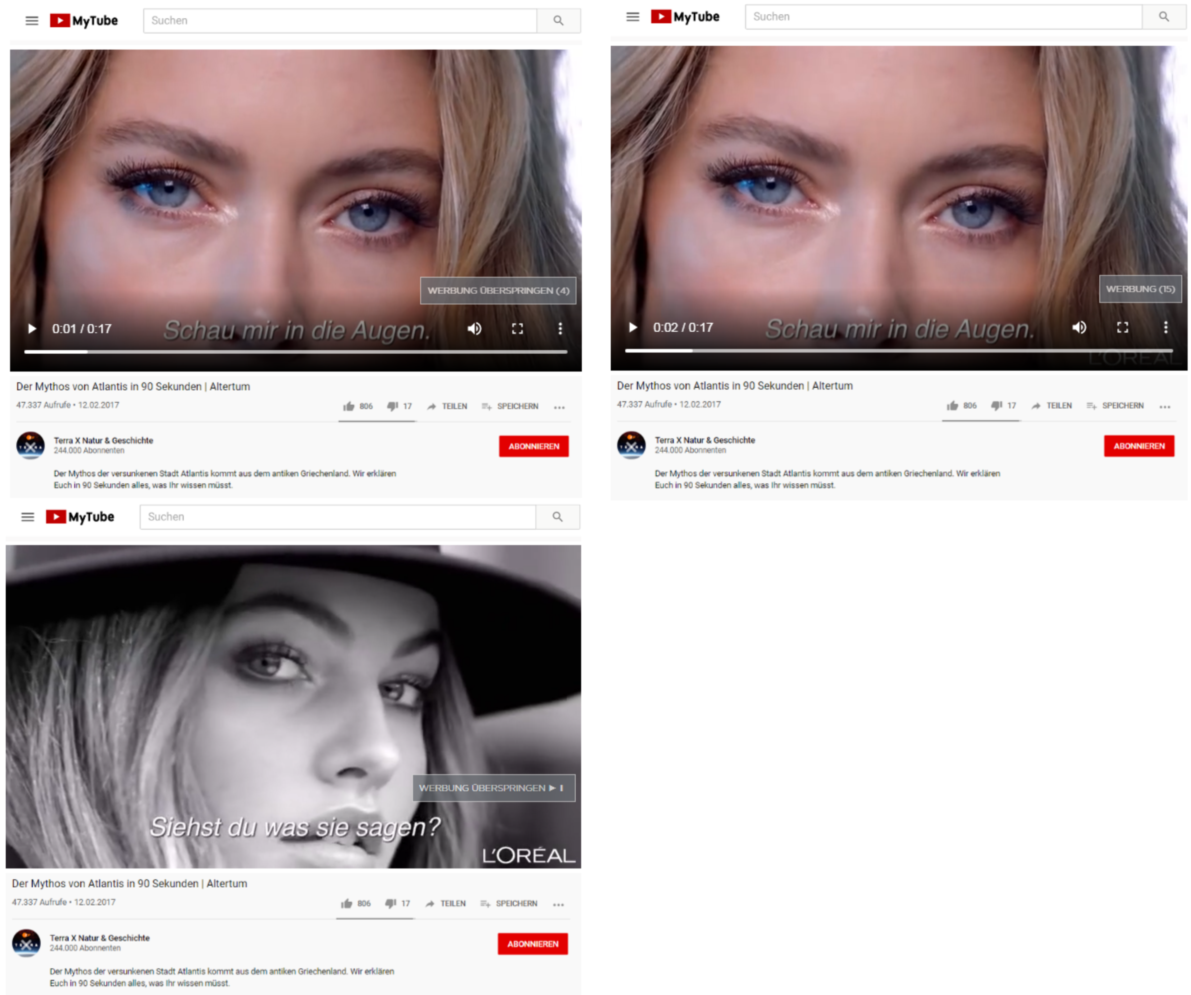
Complementing with non-skippable ads. Although all major publishers and advertising networks only offer to set up campaigns either with skippable or non-skippable ad formats, advertisers may profit from combining the two. Most advertisers try to show the ad to each consumer multiple times over the course of a campaign due to the positive effects of repeated ad exposure (Campbell and Keller 2003). Forcing the exposure during the first ad encounter ensures that the advertiser can communicate the brand message and profit from transporting the consumer through its narration. Subsequent skippable ad showings will reduce possible adverse effects of repeated ad showings (Anand and Sternthal 1990; Campbell and Keller 2003) and, thus, mitigate the intrusiveness and irritation associated with non-skippable formats. Additionally, even if a consumer skips the subsequent ad showings, their initial five seconds may still function as a memory hook, triggering the consumer to recall the complete ad and thus reinforcing the message and brand. This effect has been shown in the context of zipping ads after an initial full exposure (Bellmann, Schweda, and Varan 2010; Gilmore and Secunda 1993). Therefore, I expect that combining skippable and non-skippable ad formats, specifically by forcing exposure during the first ad encounter and allowing consumers to skip subsequent ad encounters has the potential to combine the best of both worlds while mitigating their respective weaknesses.

5 Study overview

In order to address my research questions, I designed three laboratory studies that replicate online video content consumption scenarios that are interrupted by video ads. Subjects are instructed to imagine a scenario in which they want to watch content videos on an online video platform. These content videos are preceded by pre-roll video ads. As soon as an ad ends, the content video starts automatically. The designs are reminiscent of market leader YouTube to ensure that the subjects are familiar with the situation. Across all studies, in the skippable ad condition, the skip button is initially deactivated and features a timer that counts down the five seconds that the subjects need to wait before she is allowed to skip the ad. In the non-skippable condition, a deactivated button that shows a countdown for the entire length of the ad is displayed in the same place. Subjects are always able to observe the duration of the ad by means of a progress bar. An example of this implementation is presented in Figure 2. The experiments are followed by questionnaires that allow me to assess the between-subject differences in the perception of the ad and brand outcomes. I also measure whether and when subjects skipped the ad. A laboratory study is well-suited to pursue my research goal because it allows me to tightly control confounding factors and to administer the exhaustive questionnaire necessary to assess the various constructs of the underlying process, which would be difficult to implement in the field.

Figure 2: Manipulation of Skippability

Skippable ad | Non-skippable ad



Study 1 compares three different ad formats and their effects on subjects' perceived irritation: a non-skippable 30-second ad, a skippable 30-second ad, and a non-skippable 6-second ad. This design allows me to find out how skippability, (i.e. whether the ad is skippable

versus non-skippable), skipping, and ad length influence consumers' ad perceptions. I also categorize and analyze subjects based on their viewing behavior, meaning whether they skipped (Skippers), watched the ad voluntarily (Voluntary Viewers), or were forced to watch the ad (Forced Viewers). Thus, I can compare forced to voluntary exposure and uncover possible self-selection effects associated with skipping.

In *Study 2*, I employ a 2x2 design comparing skippable and non-skippable ads that feature the brand and product either within the first five seconds (high brand visibility) or at the end of the ad (low brand visibility). In this way, I manipulate whether the ad is more commercially (high brand visibility) or narration (low brand visibility) focused and, thus, to which degree the ad is able to transport the viewer (Van Laer et al. 2014). I, thereby, uncover how ads' commercial focus by means of brand visibility moderates the effectiveness of skippable versus non-skippable OVA. Also, while Study 1 focuses on irritation, Study 2 includes brand outcomes in the form of brand and product attitudes as well as brand recall and purchase intention. Additionally, I use the results to replicate my findings from Study 1.

Table 1: Study Overview

Study	Focus	Main DV(s)	Focal IV(s)	Outcome Variable(s)
1	Uncovering the underlying process	• Control • Intrusiveness • Entertainment • Ad Attitude	• Ad Formats • Viewer Types • Skipping	• Irritation
2	• Replication of Study 1 • Analysis of the moderating effect of brand visibility	• Control • Intrusiveness • Entertainment • Ad Attitude	• Skippability • Viewer Types • Skipping • Brand Visibility	• Irritation • Brand Attitude • Product Attitude • Brand Recall • Purchase Intention
3	Uncovering the effects of combining skippable and non-skippable ads	• Intrusiveness • Irritation • Ad Attitude	• Ad format combinations	• Irritation • Brand Attitude • Purchase Intention

In *Study 3*, I compare sequences combining skippable and non-skippable formats in several ad breaks and compare them to sequences which only feature non-skippable or skippable formats. This allows me to uncover whether the two formats complement each other, improving advertising outcomes. In Table 1, I present an overview of the three studies.

6 Study 1: Uncovering the Underlying Process

6.1 Design

Subjects are asked to imagine they are planning a trip to Peru and are watching videos on an online platform to decide whether they rather take a hiking trail or a train to the Machu Picchu sights. The subjects see two content videos which each are around two minutes long and preceded by an ad for Nestlé's ice tea brand Fuze Tea. Depending on the condition the ad is either 30 seconds long and can be skipped after five seconds (*30Skip*), 30 seconds long and cannot be skipped (*30NoSkip*), or six seconds long and cannot be skipped, called a bumper ad in the industry (*Bumper*). The two long versions of the ad are identical, whereas the bumper ad is the official bumper version of the creative and thus is not identical to the first five seconds of the 30-second ads in order to give consumers a realistic ad-viewing experience. Each subject sees the same ad and ad format twice (i.e. once before each content video), which has the advantage that each subject has the chance to evaluate the first five seconds of the ad and whether to skip or not twice. In addition, this more closely resembles a real ad viewing experience in which consumers receive the same ad multiple times over the course of a campaign.

Subjects are allocated to the respective experimental conditions randomly. However, I inflate the likelihood of being in the skippable ad condition compared to the other two conditions (50% vs. 25%), as skipping rates are usually around 65% (Arantes, Figueiredo, and Almeida 2016; MAGNA 2017). This way, a greater number of subjects belong to the group of Voluntary Viewers, which otherwise would become too small to properly analyze statistically.

6.2 Data

A total of 264 subjects finished the study of which I excluded 30 who did not meet the control questions which asked subjects whether they had the opportunity to skip the ad and whether they answered the survey diligently. This leaves me with a total of 234 respondents of which 50 were allocated to the Bumper, 123 to the 30Skip, and 61 to the 30NoSkip conditions. The mean age of respondents is 31.85 years with 65% being female, 33% male, and the remaining 2% indicating another or not disclosing their gender.

6.3 Measures

To measure the focal constructs, I resort to established scales from the academic literature. For *intrusiveness*, I use the well-established seven-item Likert scale by Li, Edwards, and Lee (2002). *Irritation* is measured by Wells, Leavitt, and McConville's (1971) five-item Likert scale previously used in similar settings (Edwards, Li, and Lee 2002) and for perceived user *control*, I use Gao, Rau, and Salvendy's (2010) three-item Likert scale, which the authors developed for interactive advertisements. I measure the ad's *entertainment* value using Ducoffe's (1995) three-item Likert scale. Following the recommendation in Bergkvist and Rossiter (2007), I use Haley and Baldinger's (1991) single-item scale to measure *ad attitude*. All items were measured using five-point scales.

The confirmatory factor analysis (CFA) of the measurement model for this study fits the data well ($\chi2$ [195] = 389.249, CFI = 0.898, TLI = 0.879, RMSEA = .095, SRMR = .063). Convergent validity is indicated by the standardized factor loadings, which all exceed .60 and are significant at the .1% level. The average variance extracted (AVE) for each construct is greater than .50 and the composite reliability scores, as well as Cronbach's alphas, are consistently larger than .80, indicating reliable and valid constructs.

6.4 Results

65% of subjects in the 30Skip condition skipped the ad on both occasions while 35% watched the ad once. None of the respondents in the 30Skip condition watched the ad completely twice. During the first ad showing, 46% of subjects in the 30Skip condition skipped within five seconds of the skip button being activated and 66% skip within the first half of the ad. Hence, subjects' skipping behavior closely resembles earlier findings from field data (Arantes, Figueiredo, and Almeida 2016; MAGNA 2017).

The effect of skippability. I first compare the three conditions using a MANOVA for all five constructs, i.e. perceived control, intrusiveness, entertainment, ad attitude, and irritation, which indicates highly significant differences among ad formats ($F(10, 454) = 4.689$, $p < .001$). I subsequently use separate ANOVAs on each construct with Tukey's post-hoc tests for homoscedastic and Games-Howell tests for heteroscedastic group variances.

Subjects in the 30Skip condition perceive a significantly higher level of control ($M = 2.6$, $SD = 1.1$, $p = .018$) than subjects in the Bumper ($M = 1.8$, $SD = .74$, $p < .001$) and 30NoSkip ($M = 1.8$, $SD = .91$, $p < .001$) conditions, whereas the Bumper and 30NoSkip conditions do not differ significantly ($p = .894$). Despite differences in control and length, the three ad formats neither differ significantly in terms of intrusiveness ($F(2, 231) = 2.23$, $p = .269$) nor irritation ($F(2, 231) = 1.21$; $p = .299$). However, the ad format marginally influences subjects' attitude towards the ad ($F(2, 231) = 2.83$, $p = .061$) with those in the 30NoSkip condition ($M = 2.90$, $SD = 1.0$) reporting a significantly higher attitude towards the ad than subjects in the 30Skip condition ($M = 2.6$, $SD = .88$, $p=.048$).

To control for interdependence between the constructs and their joint effect on irritation, I construct a mediation model in line with the first part of the conceptual framework in Figure 1, i.e. excluding brand outcomes for now. In addition to the effects depicted in Figure 1, I specify direct effects from control, entertainment, and skippability on irritation in order to conservatively allowing for paths that may be unaccounted for by the current framework. For parsimony and interpretability, I exclude the bumper condition, allowing me to directly compare skippable to non-skippable formats. The resulting covariance-based structural equation model (SEM) is estimated with bootstrapped standard errors based on 10,000 bootstraps ($\chi 2$ [3] = 6.281, CFI = 0.985, RMSEA = .077, SRMR = .038). I report standardized coefficients to allow for better comparability with the replication results in Study 2, which is based on 7-point Likert scales, whereas Study 1 uses 5-point Likert scales.

The mediation model reveals the two suggested opposing forces in skippable ads that are equally strong: There is an indirect path through perceived control that *decreases* irritation (β = -.055, p = .044) as well as an indirect path through ad attitude that *increases* irritation (β = .053, p = .029), resulting in a total effect of skippability on irritation that is not significantly different from zero (β = .079, p = .294). The direct path from skippability on irritation is fully mediated through the indirect effects (β = .050, p = .78).

On a more granular level, I find that the decrease in irritation is driven by the positive effect of skippability on perceived control (β = .321, p < .001), which in turn decreases irritation (β = -.171, p = .02). Contrary to my expectations, neither skippability nor control significantly reduce intrusiveness. Together with the prior ANOVA results, this suggests that users perceive all kinds of ad breaks as intrusive, irrespective of their length or their skippability. The positive indirect path is caused by the highly significant negative effect of skippability on subjects' attitude towards the ad (β = -.159, p < .001), which, in turn, is associated with a significant decrease in irritation (β = -.335, p < .001), thus causing irritation to increase as a result of the lower ad attitude associated with skippable ads. In addition and in line with Edwards, Li, and Lee (2002), I find that entertainment decreases intrusiveness (β = -.288, p < .001).

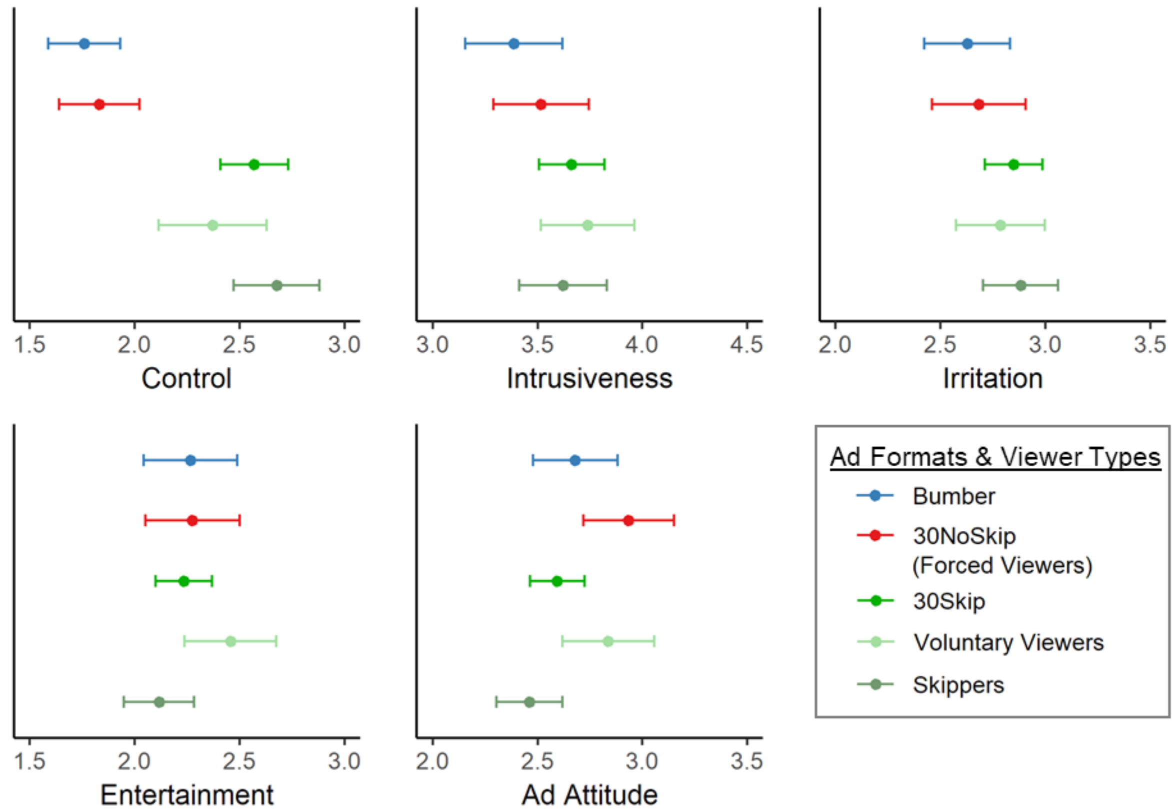
The effect of skipping. So far, I have restricted the analysis to comparing ad formats, irrespective of whether a subject actually skipped or not. In order to analyze how actual skipping influences subjects' ad perceptions, I use the two conditions with 30-second ads and differentiate subjects based on whether they skipped the ad (Skippers), watched it although they had the opportunity to skip (Voluntary Viewers), or were forced to watch the ad (Forced Viewers). Subjects can skip the ad any time after the initial five seconds, even right before the ad would have ended anyway. Therefore, I classify their skipping behavior not based on whether they clicked the skip button or not but rather by how much of the ad they have watched. I define skipping as watching less than 50% of the ad.

A total of 80 subjects skipped both ads, classifying them as Skippers, while 44 Voluntary Viewers watched the ad at least once although they had the opportunity to skip. The 61 subjects in condition 30NoSkip who were not able to skip the ad represent Forced Viewers. Their means and confidence intervals are presented alongside the three ad format conditions for each of the constructs in Figure 3.

The MANOVA of the five constructs on viewer types is significant ($F(10, 354) = 3.904$, $p < .001$) and the subsequent ANOVAs with Tukey post-hoc tests reveal significant differences for perceived control ($F(2, 181) = 11.755$, $p < .001$) and ad attitude ($F(2, 181) = 5.110$, $p = .007$). Quite naturally, Forced Viewers ($M = 1.8$, $SD = .910$) perceive significantly lower levels of control than Skippers ($M = 2.7$, $SD = 1.10$, $p < .001$) and Voluntary Viewers ($M = 2.4$, $SD = 1.0$, $p = .024$), while the latter two do not differ significantly. For ad attitude, I find that Voluntary Viewers ($M = 2.8$, $SD = .87$) like the ad marginally more than Skippers ($M = 2.5$, $SD = .86$, $p = .082$). However, the same holds for Forced Viewers ($M = 2.9$, $SD = 1.00$, $p = .008$) while attitude towards the ad of Voluntary Viewers and Forced Viewers is virtually identical ($p = .857$). These results are intriguing because one might expect that users skip because they do not like the ad or keep watching the ad because they do like it. In this case, one would expect to see a significant difference in attitude towards the ad between Skippers and Voluntary Viewers with Forced Viewers falling somewhere in between the two because Forced

Viewers are made up of both types of viewers, Skippers and Voluntary Viewers, who, however, are simply not allowed to skip. While I indeed find that Voluntary Viewers like the ad significantly better than Skippers, Forced Viewers do not fall in between the two but show a significantly higher attitude towards the ad than Skippers, too, and the same ad attitude as Voluntary Viewers. Hence, the results imply that the very act of skipping an ad may decrease the attitude towards the ad.

Figure 3: Differences in Ad Perception among Ad Formats and Viewer Types



Means and 10% confidence intervals of the focal constructs for conditions and viewer types.

These findings already strongly suggest that skipping itself indeed changes how subjects perceive the ad and that differences in ad perceptions between Voluntary Viewers and Skippers are not purely driven by self-selection effects.

To further substantiate this finding, I explicitly test for the effect of skipping on ad perceptions. To do so, I need to address the implied simultaneity bias: Subjects may skip the ad because they do not like it but, as argued above, by skipping their ad perception may deteriorate.

Hence, a reinforcing feedback loop would arise in which a worse ad attitude leads to skipping, which, in turn, decreases ad attitude.

I create two groups, Skippers and Viewers with the latter consisting of both, Voluntary Viewers and Forced Viewers. I then estimate the effect of skipping (i.e. being a Skipper) on subjects' ad perceptions using an instrumental variable (IV) approach and 2SLS estimation. As an instrument, I use the skippability condition itself, i.e. whether the subject is in the skippable or the non-skippable condition because it is strictly exogenous and has a strong effect on whether a subject skips or not. One might argue that the condition also affects attitude towards the ad by granting the user control so that she can enjoy the ad more and that her empowerment may exercise a halo effect on her attitude towards the ad. I control for this by adding perceived control as an independent variable. Accordingly,

$$(1) \qquad \widehat{Skipping} = \gamma_0 + \gamma_1 * Skippability + \nu_1$$

$$(2) \qquad y = \beta_0 + \beta_1 * \widehat{Skipping} + \beta_2 * Control + \nu_2.$$

For ad attitude, the F-test for instrument strength confirms the validity of the IV ($p_F < 0.001$) and the Durbin-Wu-Hausman (DWH) test is insignificant (p_{DWH}=.562) indicating that simultaneity bias does not occur and that the naïve OLS estimate is consistent. According to the estimate, skipping an ad indeed exercises a significant negative effect on ad attitude (β_{OLS} = -.486, p<.001). The same pattern emerges for the effect of skipping on entertainment (β_{OLS} = -.352, p=.016; $p_F < 0.001$, p_{DWH} = .665) whereas irritation increases through skipping (β_{OLS} = .273, p=.067; $p_F < 0.001$, p_{DWH} = .242). In contrast, skipping does not seem to affect intrusiveness or vice versa (β_{OLS} = .02, p=.902; $p_F < 0.001$, p_{DWH} = .219).

6.5 Discussion

Study 1 reveals several interesting findings. First, despite their varying lengths and levels of control, the advertising formats do not differ significantly in terms of their intrusiveness. While granting users the ability to skip the ad increases their perceived control, this empowerment does not translate into a reduction in intrusiveness. Instead, any kind of ad interruption seems to elicit feelings of intrusion. The subsequent SEM indeed shows that skippability leads to the emergence of the expected two paths that determine the overall perceived irritation of the ad with opposing signs that cancel each other out on aggregate. The increased control of having the option to skip leads to a reduction in irritation, while the increased skipping that comes along with the presence of a skip button leads to a reduced attitude towards the ad, which in turn increases irritation.

The IV approach suggests that it is indeed the act of skipping that leads to the adverse effects on entertainment, attitude towards the ad, and irritation and not the other way around. This is also supported by the comparison of viewer types: Voluntary Viewers' and Forced Viewers' attitudes towards the ad are not significantly different from each other but both perceive a significantly higher ad attitude than Skippers. Hence, the results suggest that, in line with expectations, skipping leads to a disruption of the ad viewing and transportation experience, deteriorating subjects' enjoyment of the ad and increasing irritation.

7 Study 2: The Moderating Effect of Brand Visibility

7.1 Design

Subjects are told they are part of an experiment that evaluates how consumers perceive educational content on online video platforms. They are asked to watch two 90 seconds long educational videos. Both content videos are preceded by 17 seconds long pre-roll ads for mascara by L'Oréal Paris. The study employs a 2x2 design in that a) subjects can either skip the ad or not (skippability) and b) the ad features the brand and the product within the first five seconds of the ad or not (brand visibility). I use the same ad creative in all conditions but manipulate it to either highlight the brand as well as product or not. Great care was taken to achieve a seamless manipulation as is evident from the comparison of the two creatives presented in Figure A1 in the appendix. The experiment was followed by a questionnaire on the ad perception and brand outcome constructs and a debriefing of subjects.

7.2 Data

I acquired a total of 321 subjects for Study 2 of which I excluded 19 due to incorrect responses to control questions. 35% of respondents were men, 63% women, and 2% with a different or undisclosed gender. Age was inquired in terms of age brackets. The largest age brackets are 18-29 years with 77% of respondents followed by the 30-39 years with 11%.

7.3 Measures

I use the same measures as in Study 1. Additionally, I measured two more control variables in the form of subjects' general attitude towards online advertising based on Cho's (2003) seven-item Likert scale as well as subjects' product category interest based on a five-item scale that combines items from Smith and colleagues (2007) as well as Teixeira and colleagues (2014). Furthermore, I measure four brand outcome variables. Brand and product attitudes are based on McKenzie and Lutz's (1989) well-established three-item semantic differential scale. Additionally, I assess purchase intention using a single-item scale (Morrison 1979; Goodrich, Schiller, and Galletta 2015) and brand recall through a dichotomous measure (Hartnett, Romaniuk, and Kennedy 2016). Contrary, to Study 1, all items were measured on seven-point scales to allow for more nuanced responses.

My measurement model fits the data well ($\chi2$ [414] = 794.106, CFI = 0.925, TLI = 0.915, RMSEA = .055, SRMR = .061). Its standardized factor loadings exceed .50 and are significant at the .1% level with the exception of one item from the general attitude towards online advertising construct which has a factor loading of .367. The AVE exceeds .50 for all constructs, again except for general attitude towards online advertising for which the AVE is 0.378. The composite reliability scores, as well as Cronbach's alphas, are consistently larger than .80, except for control, which achieves a slightly lower composite reliability of .724 and

Cronbach's alpha of .673. Therefore, I scrutinize the control construct with Omega- (McDonald 1999) and Greatest Lower Bound- (Woodhouse and Jackson 1977) tests that mitigate some of the well-known shortcomings of Cronbach's alpha (Sijtsman 2009; Trizano-Hermosilla and Alvarado 2016). The results, $\omega = .73$ and GLB = .76, both exceed the common threshold of .70, signifying that the items reliably measure the construct. As the general attitude towards online ads construct performs well in terms of Cronbach's alpha and because I only use it as a control variable in some of my estimations, I am not concerned with the observed deviations from optimal factor loading and AVE scores.

7.4 Results

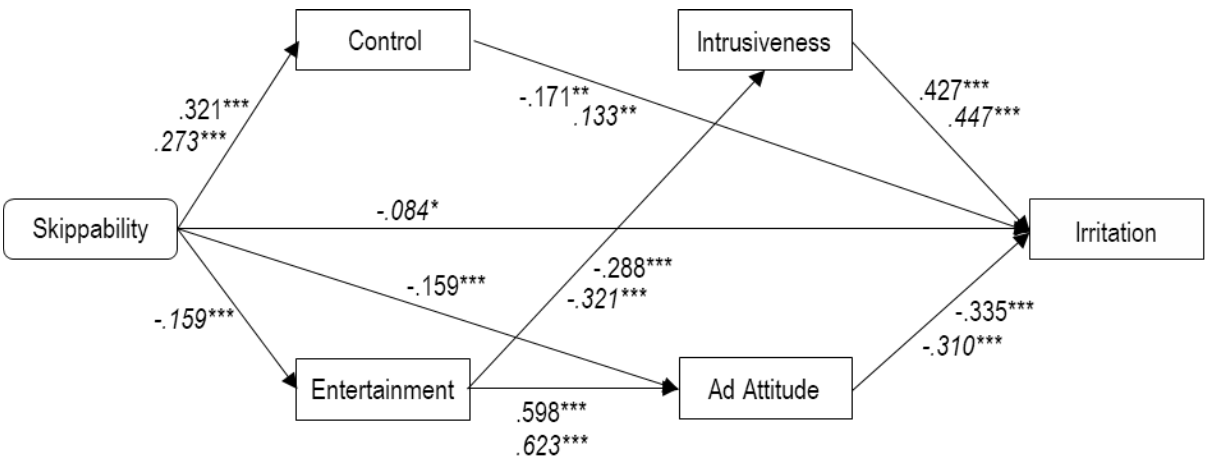
Of those subjects that had the option to skip the ad, 72% skipped both ad exposures, while the remaining 28% watched the ad at least once, and a total of six subjects watched the ad twice. Hence, the subjects skipping behavior closely resembles that of Study 1 as well as skipping behavior observed in the field (Arantes, Figueiredo, and Almeida 2016; MAGNA 2017).

Replication of Study 1. As a replication of the findings in Study 1 in construct the same mediation model. I report and present the results using standardized coefficients to allow for a better comparison between the two studies because Study 1 employed five-point whereas Study 2 used seven-point Likert scales. Figure 4 presents an overview of the significant effects and indirect effects from both studies with results from Study 1 (Study 2) printed in regular (italic) font. The complete results table is listed in Table A1 in the appendix.

Similar to Study 1, indirect paths emerge that significantly increase irritation through the perception of the ad creative. On the one hand, skippability affects entertainment ($\beta = -.159$, $p = .005$), which influences ad attitude ($\beta = .623$, $p < .001$), and in turn affects irritation ($\beta = -.310$, $p < .001$). On the other hand, entertainment decreases intrusiveness ($\beta = -.321$, $p < .001$), which, in turn, is positively related to irritation ($\beta = .447$, $p < .001$). Both these indirect paths lead to a significant increase in irritation ($\beta = .031$, $p = .017$ and $\beta = .023$, $p = .026$, respectively).

The indirect path to irritation through control from Study 1 also appears in Study 2, however with reversed signs. This means, although skippability significantly increases perceived control (β = .273, p < .001), higher control is associated with an *increase* in irritation (β = .133, p = .015) resulting in a positive indirect path (β = .036, p=.028). We further investigate this finding in a later part of the analysis. Additionally, skippability has a direct negative effect on irritation (β = -.084, p=.091) that balances out the positive indirect effects leading to an insignificant total effect of skippability on irritation (β = -.032, p=.586). This, again, demonstrates that skippable ads are not necessarily perceived as less irritating than regular non-skippable ads.

Figure 4: The Opposing Effects of Skippability on Consumers' Ad Perception



Indirect Paths		
Skippability → Control → Irritation	-.055 **	(-2.013)
Skippability → Ad Attitude → Irritation	.053 **	(2.178)
Total Effect	.079	(1.050)
Skippability → Control → Irritation	*.036 **	*(2.192)*
Skippability → Entertainment → Intrusiveness → Irritation	*.023 **	*(2.223)*
Skippability → Entertainment → Ad Attitude → Irritation	*.031 **	*(2.388)*
Total Effect	*-.032*	*(-.544)*

$\chi2$ [3] = 6.281, CFI = 0.985, RMSEA = .077, SRMR = .038
$\chi2$ [3] = 34.057, CFI = 0.916, RMSEA = .185, SRMR = .057

Standardized coefficients of the mediation model. Results of Study 1 in regular font, results of Study 2 in italic.
* p < .10, ** p < .05, *** p < .001

To substantiate my earlier findings that the act of skipping causes the deterioration of subjects' ad perception, I replicate the IV approach from Study 1. In addition to subjects' perceived control, I include their attitude towards online ads and their product category interest as control variables. Again, I use the condition as the IV, which according to the F-test is a strong instrument in all of the regressions ($p_F < .001$). Just as before, I find a significant negative effect of skipping on ad attitude (β_{OLS} = -.278, p = .082). The DWH-test on the 2SLS versus OLS model is insignificant (p_{DWH} = .426) suggesting that there is no simultaneity causing ad attitude to influence skipping. In terms of entertainment, the DWH-test is significant (p_{DWH} = .006) implying that entertainment has an influence on skipping. The endogeneity corrected coefficient with robust standard error reveals that skipping significantly decreases entertainment (β_{2SLS} = -.638, p > .001). I do not find significant effects for skipping on intrusiveness (β_{2SLS} = .091, p = .672) and irritation (β_{2SLS} = -.282, p = .202). An overview of these results alongside those of Study 1 is presented in Table 2 with values in regular font representing results form Study 1 and values in italic signifying results from Study 2. Although some small differences exist in relation to Study 1, Study 2 replicates and substantiates the prior findings.

Table 2: The Effects of Skipping on Ad Perception

Dependent Variables	Skipping Coefficient (t-value)		Instrument Strength		DWH-Test	
Entertainment	β_{OLS} = -.352**	(-2.421)	154.523	(p < .001)	.188	(p = .665)
	*β_{2SLS} = -.638****	*(-3.689)*	*366.319*	*(p < .001)*	*7.58*	*(p = .006)*
Ad Attitude	β_{OLS} = -.478***	(-3.358)	154.523	(p < .001)	.573	(p = .45)
	*β_{OLS} = -.278**	*(-1.747)*	*366.319*	*(p < .001)*	*.635*	*(p = .426)*
Intrusiveness	β_{OLS} = .021	(.123)	154.523	(p < .001)	1.519	(p = .219)
	β_{2SLS} = .091	*(.423)*	*366.319*	*(p < .001)*	*5.435*	*(p = .02)*
Irritation	β_{OLS} = .273*	(1.845)	154.523	(p < .001)	1.38	(p = .242)
	β_{2SLS} = -.282	*(-1.28)*	*366.319*	*(p < .001)*	*2.834*	*(p = .093)*

Results of Study 1 / Study 2 in regular / italic font.
Instrumental variable (IV) strength based on F-test. DWH: Durbin-Wu-Hausman.
* p < .10, ** p < .05, *** p < .001

The moderating effect of brand visibility. Next, I turn my attention to the second dimension of this study, i.e. brand visibility during the first five seconds of the ad. Beyond irritation, I also analyze the impact on product and brand attitudes, purchase intentions, and brand recall.

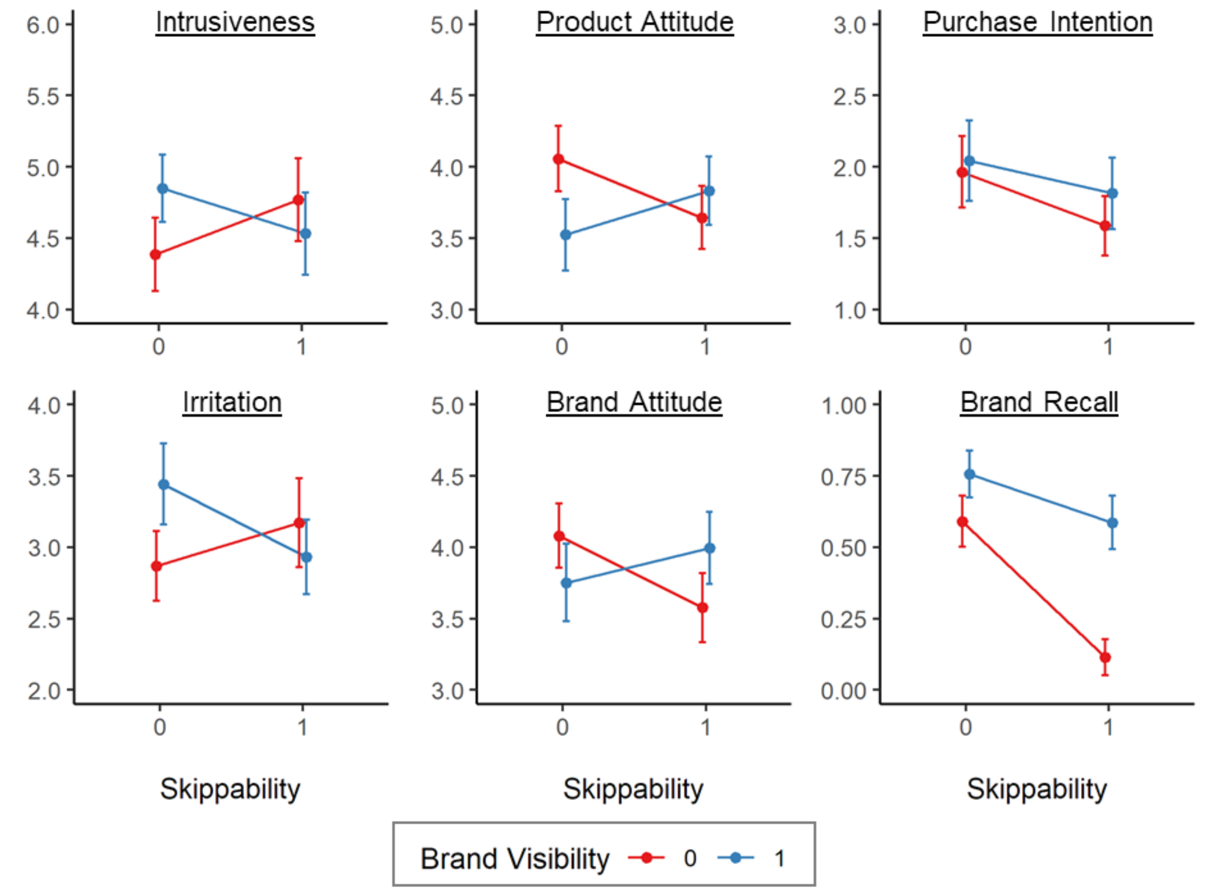
Using a logit regression, I find that neither consumers' product category interest nor gender—or in other words subjects' target group affiliation—significantly decreases skipping; irrespective of the level of brand visibility. Brand visbility, in turn, neither significantly moderates nor directly affects skipping. Hence, a large portion of a brand's target audience ends up skipping ads, which means that it is crucial that advertisers make sure they effectively deliver their message even to those consumers that skip.

The MANOVA on the ad perception and brand outcome constructs finds significant effects for skippability ($F(8, 291) = 10.607$, $p < .001$), brand visibility ($F(8, 291) = 5.517$, $p < .001$), as well as their interaction ($F(8, 291) = 2.069$, $p = .039$). Hence, given that the covariates are binomial, I run individual OLS interaction models for each construct. Interaction plots for skippability and brand visibility are presented in Figure 5.

Brand visibility and its interaction with skippability have no significant effect on subjects' perceived control, entertainment, and ad attitude, but it significantly increases users' perceived intrusiveness ($\beta = .464$, $p = .042$). This effect is reversed, however, for the interaction effect ($\beta = -.702$ $p = .033$). Hence, in non-skippable conditions, ads with low brand visibility are perceived as less intrusive whereas in skippable conditions, high brand visibility is perceived as less intrusive. The same holds true for irritation in that brand visibility by itself increases irritation ($\beta = .576$, $p = .014$) but in the context of skippability reduces irritation ($\beta = -.817$, $p = .015$).

Brand visibility also influences brand outcomes. Skippability has a negative effect on product ($\beta = -.413$, $p = .042$) and brand attitude ($\beta = -.504$, $p = .018$), while brand visibility only significantly affects product attitude ($\beta = -.534$, $p = .008$). Again, this effect is reversed through the interaction effect between skippability and brand visibility, meaning that product attitude ($\beta = .747$, $p = .014$) and brand attitude ($\beta = .722$, $p = .013$) are both elevated by an early brand visibility in skippable ads, whereas brand visibility in non-skippable ads reduces subjects' product and brand attitudes. In terms of purchase intention, I find a significant negative average effect of skippability (β = -.378, p = .08), but no effect of brand visibility (β = .077, p = .718) or its interaction with skippability (β = .151, p = .622). The incremental effects for the probability of recalling the advertised brand show that low brand visibility significantly increases brand recall (β = .158, p = .031) while it decreases drastically through skippability (β = -.461, p < .001). This strong negative effect, however, is mitigated when brand visibility in skippable ads is high (β = .282, p < .001).

Figure 5: Interaction Effects of Skippability and Brand Visibility



Figures show means and 10% confidence intervals.

In order to assess the overall effects of skippability and brand visibility on consumers' ad and ultimately product and brand perception, I implement the full mediation model as depicted in the conceptual framework. I include brand and product attitude as outcome variables and, given their interdependence, allow for correlation between their residuals. Brand visibility is introduced as a moderator. In order to keep the model parsimonious and avoid multicollinearity issues through a large number of interaction effects, I estimate two models: one for the two conditions with low brand visibility ($\chi2$ [5] = 24.412, CFI = 0.957, RMSEA = .159, SRMR = .057) and one for the two conditions with high brand visibility ($\chi2$ [5] = 35.373, CFI = 0.94, RMSEA = .202, SRMR = .059) using 10,000 bootstraps for each. I present the results in Table 3. The constructs in italics are the dependent variables of the model's respective part while constructs in regular font are the independent variables. Moving from the bottom of the table to the top represents a progression from left to right in terms of the conceptual model. Accordingly, the effects of skippability on entertainment and control are found in the lower part of the table, while the effects on the outcome variables are at the top of the table. Significant coefficients are highlighted in bold.

The differences between the two models show that brand visibility significantly moderates the effectiveness of skippable ads in comparison to non-skippable ads. Specifically, in the low brand visibility model the total effects of skippability on brand and product attitudes are significant and negative (β_{PA} = -.413, p = .031; β_{BA} = -.504, p = .011), whereas in the high brand visibility model, the total effects do not differ significantly between skippable and non-skippable ads (β_{PA} = .309, p = .144; β_{BA} = .243, p = .281). Hence, when brand visibility is low, skippable ads perform significantly worse than non-skippable ads, while high brand visibility negates this difference. In the low brand visibility setting, the negative total effect is driven by an indirect negative path from skippability to product and brand attitude through entertainment and ad attitude (β_{PA} = -.113, p = .034; β_{BA} = -.125, p = .016). In contrast in the high brand visibility model, I find a positive indirect path through irritation β_{PA} = .134, p = .058; β_{BA} = .157, p = .048).

Table 3: Effects of Skippability and Brand Visibility on Ad and Brand Perceptions

	Low Brand Visibility		High Brand Visibility	
Brand Attitude				
Irritation	-.192 **	(-2.262)	-.395 ***	(-5.731)
Control	-.145 **	(-2.271)	.054	(0.701)
Intrusiveness	-.013	(-0.158)	.005	(0.075)
Ad Attitude	.339 ***	(5.347)	.365 ***	(6.074)
Skippability	-.251	(-1.465)	-.024	(-0.141)
Product Attitude				
Irritation	-.156 *	(-1.87)	-.337 ***	(-4.123)
Control	-.106 *	(-1.655)	.111	(1.333)
Intrusiveness	.009	(0.099)	-.009	(-0.12)
Ad Attitude	.305 ***	(4.229)	.332 ***	(5.205)
Skippability	-.213	(-1.252)	.019	(0.115)
Irritation				
Control	.210 ***	(2.601)	.018	(0.217)
Intrusiveness	.601 ***	(8.211)	.272 ***	(3.685)
Skippability	-.059	(-0.288)	-.396 **	(-2.039)
Entertainment	.090	(0.91)	.070	(0.603)
Ad Attitude	-.168 **	(-2.028)	-.499 ***	(-5.167)
Intrusiveness				
Skippability	.189	(0.811)	-.437 **	(-2.113)
Control	-.055	(-0.647)	.053	(0.522)
Entertainment	-.440 ***	(-4.576)	-.314 ***	(-3.033)
Ad Attitude				
Skippability	.070	(0.351)	.250	(1.388)
Entertainment	.713 ***	(8.491)	.822 ***	(10.749)
Control				
Skippability	.610 ***	(2.693)	.854 ***	(4.369)
Entertainment				
Skippability	-.518 ***	(-2.769)	-.234	(-1.224)
Indirect paths				
	Skip. → Enter. → Ad Att. → Brand Att.		Skip. → Irritation → Brand Att.	
	-.125 **	(-2.406)	.157 **	(1.979)
	Skip. → Enter. → Ad Att. → Product Att.		Skip. → Irritation → Product Att.	
	-.113 **	(-2.118)	.134 *	(1.896)
	Total$_{BrandAttitude}$		Total$_{BrandAttitude}$	
	-.504 **	(-2.553)	.243	(1.079)
	Total$_{ProductAttitude}$		Total$_{ProductAttitude}$	
	-.413 **	(-2.156)	.309	(1.46)

LBV: $\chi2$ [5] = 24.412, CFI = 0.957, RMSEA = .159, SRMR = .057
HBV: $\chi2$ [5] = 35.373, CFI = 0.94, RMSEA = .202, SRMR = .059
Coefficients and z-values (in parentheses) for low / high brand and product visibility (LBV / HBV)
* p < .10, ** p < .05, *** p < .001 → hier noch die indirekt effects für irrit rein

Additionally, brand visibility also moderates perceived entertainment: While perceived entertainment is significantly lower in skippable than non-skippable ads (β = -.518, p = .006) when brand visibility is low, there is no such difference when brand visibility is high (β = -.234, p = .221). Thus, in line with expectations, brand visibility mitigates the negative effects of skipping on subjects' ad enjoyment. In terms of intrusiveness and irritation, the model reveals a significant effect of skippability when brand visibility is high ($\beta = -.437$, $p = .035$ and $\beta = -.396$, $p = .041$, respectively), whereas under low brand visibility it does not alleviate intrusiveness nor irritation ($\beta = .189$, $p = .417$ and $\beta = -.059$, $p = .773$, respectively). I also find the positive effect of control on irritation from earlier and in addition a negative effect on product and brand attitude. However, these effects are moderated by brand visibility, thus, only occurring under low brand visibility.

7.5 Discussion

The results from Study 2 support those from Study 1, substantiating the finding of two opposing forces that influence consumers' perception of skippable ads—on the one hand through a reduction of intrusiveness and increase in control, and on the other hand through the worse perception of the ad content. This study also further corroborates the finding that the act of skipping indeed leads to an adverse effect on ad attitude and entertainment.

This effect, however, is moderated by brand visibility during the initial, non-skippable part of a skippable ad. I discover that high brand visibility is a crucial factor influencing ad perception as well as brand attitudes and recall. The results suggest that in non-skippable ads, advertisers should use low brand visibility to reduce the commercial focus of the ad and, thus, transport and persuade the consumer more effectively (Escalas 2004a, 2004b; Van Laer et al. 2014), alleviating intrusiveness and irritation while improving brand attitudes. In contrast, in skippable ads, low brand visibility has adverse effects on ad and brand perceptions as it eliminates the negative effect of skippability on intrusiveness and irritation, decreases perceived entertainment, and causes control to adversely affect irritation and product and brand attitudes.

The results on entertainment, intrusiveness, and irritation are in line with expectations based on the higher commercial focus of a high brand visibility ad, the associated weaker transportation (Van Laer et al. 2014) and, consequently, decreased disruption due to skipping (Wang and Calder 2006). The adverse effects of higher perceived control are surprising but may be explained with the high cognitive load associated with exercising control (Ariely 2000; Brown and Krishna 2004). It increases with information and preference uncertainty as well as goal conflict which both are pronounced in skippable ads with low brand visibility as subjects cannot judge the relevance and purpose of the ad and are conflicted whether to watch the ad or not (Bettman et al. 1993; Broniarczyk and Griffin 2014). This may be amplified by the time stress induced by the short duration of the ad being perceived as a countdown that forces a decision (Etkin, Evangelidis, and Aaker 2015).

Overall, skippable ads can be as effective as non-skippable ads in terms of product and brand attitudes when brand visibility is high but perform significantly worse in regard to purchase intentions and brand recall even with high brand visibility. When skippable ads feature low brand visibility, they lead to significantly worse brand outcomes compared to non-skippable ads, especially in terms of brand attitudes, product attitudes, and brand recall. Therefore, managers should carefully weigh the intended campaign goals when choosing the ad format. For example, skippable ads may be better suited for performance, non-skippable ads for branding goals. In any case, however, they should refrain from employing a strong narrative focus at the cost of conveying the brand during the non-skippable fraction of a skippable ad.

8 Study 3: Complementary Effects of Combining Skippable and Non-Skippable Ads

8.1 Design

Subjects are asked to watch a series of three approximately 90 seconds long educational content videos. Each of the videos is preceded by 15 seconds long pre-roll ads for Cadbury chocolate. The content of the ads is identical but whether the user is able to skip the ad or not depends on the experimental condition. Subjects were either able to skip all three ad showings (SkipAll), skip none (SkipNone), skip the first two but not the last (SkipFirst), or skip the last two but not the first (SkipLast). I use three ad showings in order to again give each subject the possibility to judge whether to skip the ad or not at least twice.

8.2 Data

A total of 198 subjects completed the questionnaire. After excluding subjects that did not answer the control questions correctly, a total of 159 subjects remained with 39 subjects in the SkipAll, 47 in the SkipNone, 36 in the SkipFirst, and 31 in the SkipLast condition. The sample has an average age of 30.51 years, with 57% female, 26% male, and 17% not indicating a gender.

8.3 Measures

Study 3 uses the same constructs as before with all items being measured on seven-point scales. The CFA fits the data well ($\chi 2$ [242] = 378.071, CFI = 0.898, TLI = 0.879, RMSEA = .095, SRMR = .063). The standardized factor loadings exceed .50 and are significant at the .1% level and the constructs' AVE exceeds .50. The composite reliability scores, as well as Cronbach's alphas, are consistently larger than .80.

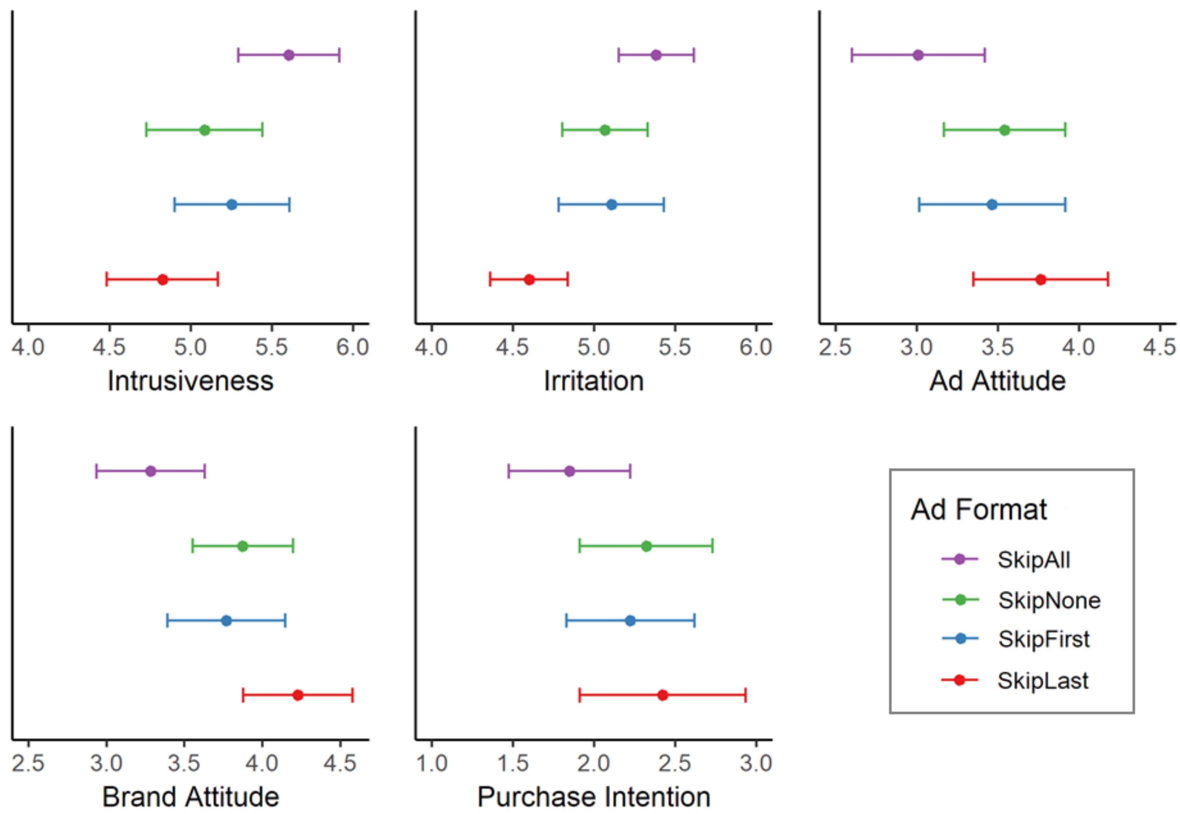
8.4 Results

In the SkipAll condition 33% of subjects skipped all three ads, 46% watched the ad once, 8% twice, and 13% watched all three ads. In the SkipFirst (SkipLast) condition, 57% (60%) skipped the ad on both occasions, 34% (20%) skipped it once, and 9% (20%) watched all ad exposures.

Using separate ANOVAs along with the appropriate post-hoc tests, I compare the four conditions in terms of how users perceive the ad. Means and confidence intervals for each construct and condition are presented in Figure 6.

In terms of intrusiveness ($F(3, 148) = 2.23$; $p = .087$) there is a significant difference between the SkipAll ($M = 5.6$, $SD = 1.2$) and SkipLast conditions ($M = 4.8$, $SD = 1.2$, $p = .036$). The same pattern emerges for irritation ($F(3, 148) = 3.46$; $p = .018$) with subjects in the SkipAll condition (M = 5.4, SD = .88) reporting a significantly higher level of irritation than those in the SkipLast condition (M = 4.6, SD = .81, p < .001).

Figure 6: Consumers' Ad and Brand Perceptions by Ad Format



Figures show means and 10% confidence intervals.

Additionally, brand attitude differs significantly between these two conditions (F(3, 148) = 5.41; p = .028), being significantly higher in the SkipLast condition (M = 4.2, SD = 1.2, p = .018) than the SkipAll condition (M = 3.3, SD = 1.3). All of these results are robust with regard to the inclusion of subjects' general attitude towards online advertising as control. Hence, in line with my expectations, the results suggest that a full ad exposure prior to skipping improves ad and brand perceptions.

To further substantiate that indeed the first exposure rather than any exposure makes a difference, I identify all subjects that have watched the ad during the first exposure, voluntarily as well as non-voluntarily. I compare them (N=66) to all other subjects that have watched the ad (N=27), but not during the first exposure. Hence, I exclude those who skipped all ad exposures and additionally exclude subjects in the SkipNone condition as their lack of control may confound the results. I again take an IV 2SLS approach in order to test and account for possible simultaneity bias. As instrument, I use a dummy for whether the first ad exposure was forced or voluntary which proves to be a strong instrument ($p_F < .001$).

I find that an initial full ad exposure indeed significantly reduces subjects' perceived irritation ($\beta_{2SLS} = -1.329$, $p = .007$; $p_{DWH} = .021$) as well as increases brand attitudes ($\beta_{2SLS} = 1.333$, $p = .042$; $p_{DWH} = .084$) compared to later ad exposures.

8.5 Discussion

In accordance with Studies 1 and 2, Study 3 shows again that non-skippable ads are perceived just as intrusive and irritating as skippable ads, even with three consecutive exposures to the same ad. Furthermore, the study shows that forced exposure may even help alleviate feelings of intrusion and irritation, and improve brand attitudes. Forcing at least one full exposure, especially during the first ad encounter, not only affects brand outcomes positively but even consumers' ad experience.

An initial full exposure allows consumers to be transported by the ad's narration without a disruption (Wang and Calder 2009). In subsequent viewings, the potential for transportation and the associated disruption through skipping then may be reduced because the consumer already knows the complete story, especially when the ads are repeated in quick succession as in this experiment. Moreover, the first five seconds of the subsequent skippable ad encounters may act as a memory hook, reinforcing the brand image and the narrative experience even when the ad is skipped, which is in line with findings from previous studies on zipped ads that follow regular ad exposures (Bellmann, Schweda, and Varan 2010; Gilmore and Secunda 1993).

9 General Discussion and Managerial Implication

My studies paint a detailed picture of the surprisingly complex processes that are underlying consumers' perception of skippable ads. I find two fundamental and opposing effects that explain why studies to date that have empirically analyzed the difference between skippable and non-skippable ads have found no significant differences in their performance (e.g. Bellmann, Schweda, and Varan 2010; Hegner et al. 2016; Pashkevich et al. 2012): Skippable ads tend to decrease irritation and improve brand outcomes through lower perceived intrusiveness and higher perceived control but at the same time increase irritation and worsen brand outcomes due to a lower enjoyment of the ad creative caused by skipping. As I show, however, this is strongly influenced by the brands' visibility in the ad. In case of low brand visibility during the initial seconds of the ad, skippable ads perform significantly worse than non-skippable ads whereas a saliently communicated brand can even counteract the usually lower enjoyment of skippable ads. Consequently, practitioners should refrain from the strategy of hiding the commercial focus of the ad in order to keep consumers from skipping. Instead, they should use a strong brand focus in skippable ads whereas non-skippable ads profit from a low brand focus in favor of a strong, transporting narration. Hence, marketers may also employ the two formats for different strategic goals: non-skippable ads in order to create and reinforce brand image and recall, and skippable ads to drive conversions.

Additionally, the findings reveal that brands, publishers, and advertising networks should not consider skippable and non-skippable as substitutes. Instead, my results show that they can be used as complements that compensate for each other's weaknesses, especially, when consumers' first ad exposure is non-skippable while subsequent exposures are skippable. In this way, brands can leverage the power of transportation through narration (Escalas 2004a, 2004b; Van Laer et al. 2014) while avoiding excessively irritating consumers, for example through high levels of ad repetition (Anand and Sternthal 1990; Campbell and Keller 2003). Additionally, this combination of ad formats may also lower advertising expenditures because publishers and advertising networks usually charge less or even nothing at all for skipped ad exposures (Pashkevich et al. 2012).

10 Limitations and Future Research

The laboratory studies allowed me to uncover the process underlying the perception of skippable ads in detail and subjects' skipping behavior closely resembled that found in the field. Nonetheless, a field study is a desirable avenue for future research in order to add external validity to the findings. After all, consumers encounter a multitude of ads in their daily (online) lives and many campaigns use substantially higher ad repetitions than my experiments. Additionally, the experiments were conducted over a time span of roughly ten minutes whereas actual campaigns usually cover several weeks. Therefore, a field study could add further depth by analyzing the effectiveness of combining skippable and non-skippable ad formats over longer periods of time and with varying numbers of ad repetitions per viewer. In longer campaigns it may be necessary, for example, to force multiple ad exposures instead of just the first in order to counteract wear out effects (Campbell and Keller 2003).

Additionally, I have excluded costs from my analysis. In practice, however, advertisers usually pay less or nothing at all for ad exposures that have been skipped by a user (Pashkevich et al. 2012). Hence, from an ROI perspective, the lower costs of skippable ads may make them more attractive to advertisers even if they are less effective. Hence, future research should take into account the cost side of the two ad formats in order to find out how they can be combined not only for maximum effectiveness but also for efficiency.

Finally, I use theoretical concepts from literature such as transportation and cognitive load that are well-suited to explain the findings. However, given the focus of this work, I have refrained from rigorously scrutinizing the extent to which they apply and which boundary conditions exist, and, therefore, encourage future research to specifically address the role of transportation and cognitive load in the context of skippable ads and advertising avoidance.

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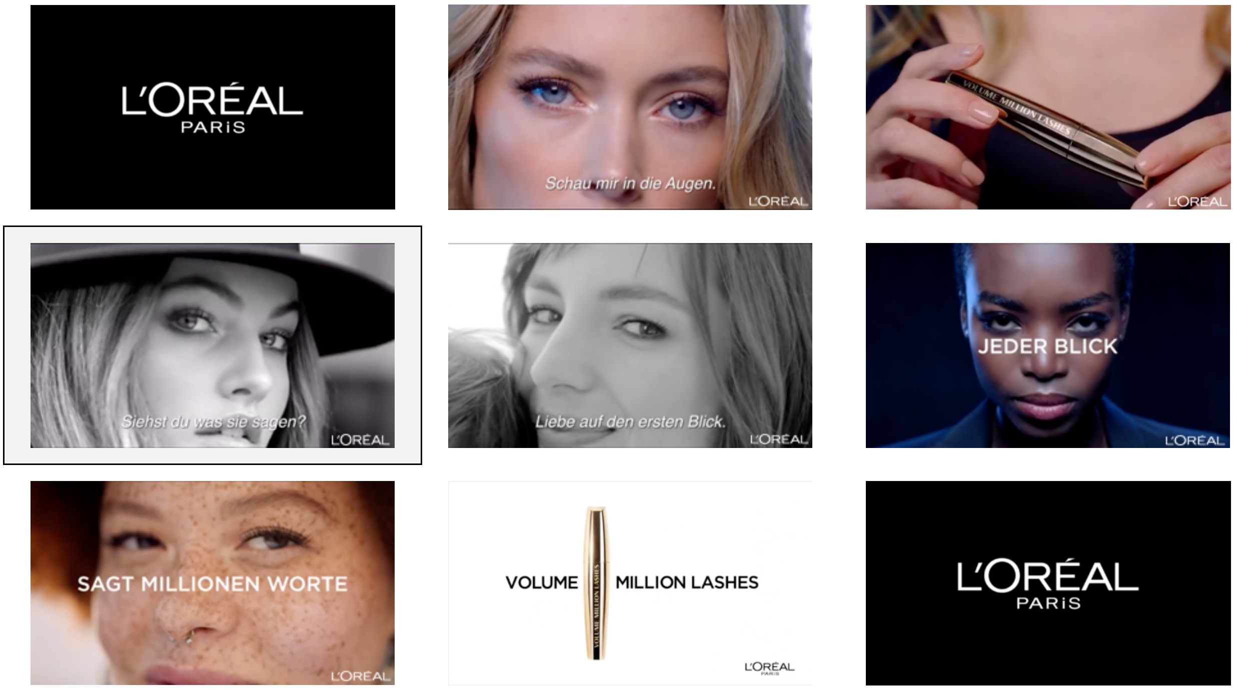
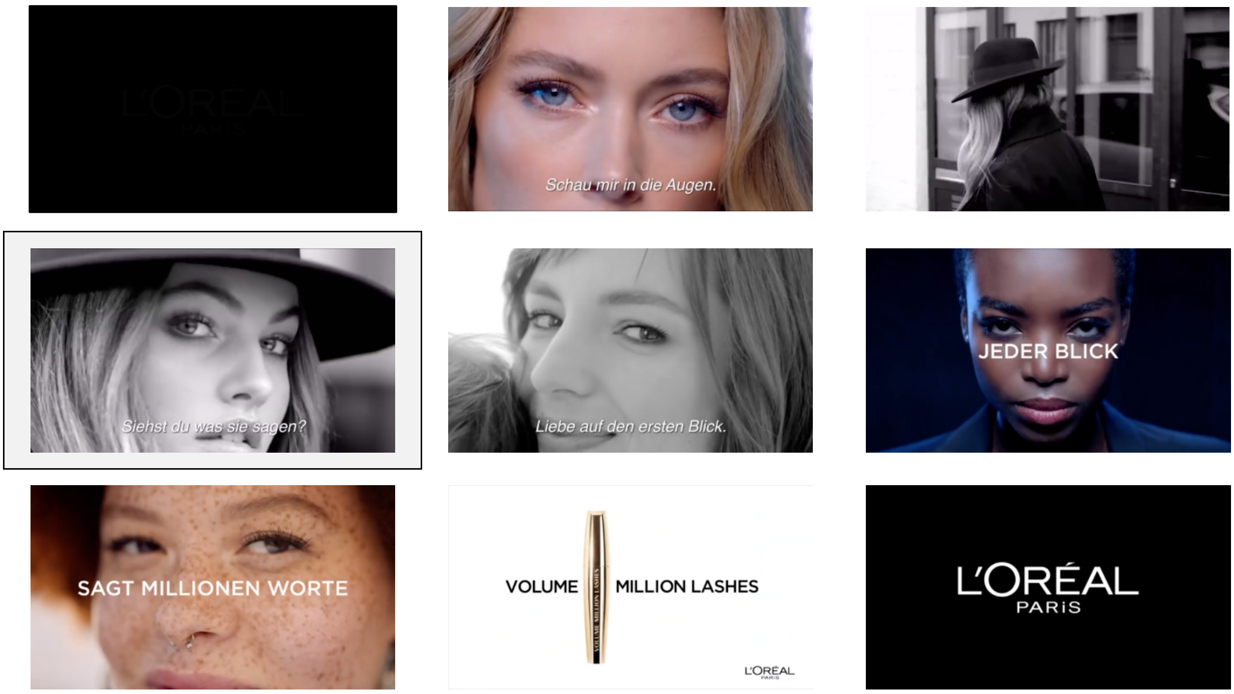
Appendix Essay III

Figure A1: Manipulation of Brand Visibility in the Creative

High brand visibility condition



Low brand visibility condition



Note: The highlighted frame depicts the five-second mark from which on subjects were able to skip the ad.

Table A1: Overview of Full SEM Results from Study 1 and 2

Independent Variables	Dependent Variables: Entertainment	Control	Ad Attitude	Intrusiveness	Irritation
Skippability	-.020 (-.256)	.321 *** (4.871)	-.159 *** (-2.828)	.053 (.686)	.050 (.780)
	*-.159 *** (-2.793)*	*.273 *** (4.827)*	*.056 (1.257)*	*-.033 (-.609)*	*-.084 * (-1.686)*
Entertainment			.598 *** (7.608)	-.288 *** (-4.076)	-.051 (-.631)
			*.623 *** (13.604)*	*-.321 *** (-5.521)*	*.028 (.433)*
Control				.020 (.263)	-.171 ** (-2.327)
				-.012 (-.203)	*.133 ** (2.425)*
Ad Attitude					-.335 *** (-3.731)
					*-.310 *** (-4.454)*
Intrusiveness					.427 *** (6.303)
					*.447 *** (8.204)*

Indirect Paths		
Skippability → Control → Irritation	-.055 **	(-2.013)
Skippability → Ad Attitude → Irritation	.053 **	(2.178)
Total Effect	.079	(1.050)
Skippability → Control → Irritation	*.036 **	*(2.192)*
Skippability → Entertainment → Intrusiveness → Irritation	*.023 **	*(2.223)*
Skippability → Entertainment → Ad Attitude → Irritation	*.031 **	*(2.388)*
Total Effect	*-.032*	*(-.544)*

$\chi 2$ [3] = 6.281, CFI = 0.985, RMSEA = .077, SRMR = .038

$\chi 2$ [3] = 34.057, CFI = 0.916, RMSEA = .185, SRMR = .057

Standardized Coefficients of the mediation model with z-values in parentheses.

Results of Study 1 in regular font, results of Study 2 in italic.

* p < .10, ** p < .05, *** p < .001