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Abstract

Psychology and economics (the mixture of which is known as behavioral economics) are two fundamental disciplines underlying marketing. Various marketing studies document the non-rational behavior of consumers, even though behavioral biases might not always be consistently termed or formally described. In this review, we identify empirical research that studies behavioral biases in marketing. We summarize the key findings according to three classes of deviations (i.e., non-standard preferences, non-standard beliefs, and non-standard decision-making) and the marketing mix instruments (i.e., product, price, place, and promotion). We thereby introduce marketing researchers to the theoretical foundation of and terminology used in behavioral economics. For scholars from behavioral economics, we provide ready access to the rich empirical, applied marketing literature. We conclude with important managerial implications resulting from the behavioral biases of consumers, and we present avenues for future research.

Keywords: Marketing, Behavioral Economics, Behavioral Biases, Review

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1. Introduction

For several decades, research in behavioral economics (i.e., the mixture of psychology and economics) has challenged the neoclassical paradigm by providing ample evidence that individual decisions are often systematically biased and do not confirm the forecasts of the standard theory (Thaler 2016). Such “behavioral biases” refer to deviations from the standard, neoclassical model that assumes that people are rational and have stable preferences, maximize expected utility (defined over final payoffs), exponentially discount future utility, process information like a Bayesian, and are purely self-interested (Rabin 2002). Behavioral scientists have been very successful in documenting those biases and in establishing new theories that formalize and explain the observed behavior, which deviates from the neoclassical model.

Despite a growing interest in behavioral economics in recent years, there has been substantial resistance to the behavioral approach within economics until relatively recently (Thaler 2016). In business research, however, and particularly in the domains of finance[1] and marketing, drawing on psychological theory has a long history and is deeply rooted in studying actual human behavior. In fact, precisely predicting human behavior to inform marketing decisions is one of the key objectives of marketing. However, even though economics and psychology are the two most influential disciplines underlying marketing (Ho, Lim, and Camerer 2006), no review has yet documented the empirical findings focusing solely on this field. Marketers in need of more theory could benefit from paying closer attention to behavioral economics, and economists could benefit from more closely following developments in marketing (e.g., developments that exploit the availability of rich consumer data documenting instances of non-rational behavior).[2]

In this paper, we aim to bring together research from behavioral economics and marketing. The objective of this paper is to identify research in marketing that analyzes behavior deviating from neoclassical predictions and to map these findings onto a structure that involves elements of both economics and marketing. We provide an overview of behavioral biases studied in the latter and demonstrate that the major biases studied in economics have also been studied in marketing, even though they might not always be consistently termed or formally described. We provide detailed summaries of selected strong examples of biases from empirical marketing research, deriving

[1] The field of behavioral finance can be considered as the most comprehensive combination of psychology and economics in a business discipline (DellaVigna 2009). A review documenting the empirical findings can be found in Barberis and Thaler (2003).

[2] http://evonomics.com/behavioraleconomics-neglect-marketing

implications for marketing research and practice. We focus on evidence from both the field and the lab. Note that, as opposed to the typically context-free lab experiments of economics, lab studies in marketing usually involve a particular marketing context and may therefore also provide interesting insights into how consumers and firms might behave under different circumstances.

This paper contributes to marketing research and practice as well as to the field of behavioral economics. The contribution to research is twofold. First, the paper provides a structured review of the behavioral biases studied in marketing contexts and published in marketing outlets. Specific biases are analyzed for each of the elements of the marketing mix (i.e., product, price, place, promotion). Thus, this paper, unlike DellaVigna's (2009) paper, in which marketing studies were undersampled, applies a thematic focus. This approach introduces marketing researchers to the (more rigorous) terminology employed in the field of behavioral economics and may thereby help them to better navigate the extensive list of documented biases in this field. Regarding the field of behavioral economics, we aim to provide scholars with easy access to the rich marketing literature that contains applied empirical research. In addition, incorporating insights from other social sciences such as marketing gives researchers the opportunity to develop better models of economic behavior.

More generally, researchers may benefit from this review by pursuing the proposed avenues for future research. With regard to marketing practice, this paper provides important implications for marketing managers by discussing how they could benefit from the non-rational behavior of their customers and how such behavior could change due to continuing technological advances.

The paper's structure reflects the goal of combining marketing and behavioral economics. We organize the paper according to the marketing mix instruments and categorize behavioral biases into three different classes following DellaVigna's (2009) review of deviations from rational behavior (non-standard preferences, non-standard beliefs, and non-standard decision making). The conceptual framework in the next section addresses the specific behavioral biases included in our review and briefly introduces the marketing mix instruments. Thereafter, we discuss selected papers that reflect the different "marketing instrument-bias" combinations, as well as managerial implications and avenues for future research. The paper concludes with general implications and a conclusion.

2. Conceptual Framework

2.1. Behavioral Biases

In this section, we introduce and briefly explain biases, which are widely covered in behavioral economics and that we discuss subsequently against the background of the marketing literature. We follow the structure of DellaVigna (2009) and distinguish deviations (i.e., behavioral biases) of individuals from the neoclassical standard model (Rabin 2002), where decision-makers are rational and have stable preferences, maximize expected utility (defined over final payoffs), exponentially discount future utility, process information like a Bayesian, and are purely self-interested. In particular, we cover three classes of deviations from this model (DellaVigna 2009): non-standard preferences, non-standard beliefs, and non-standard decision-making (see Figure 1).

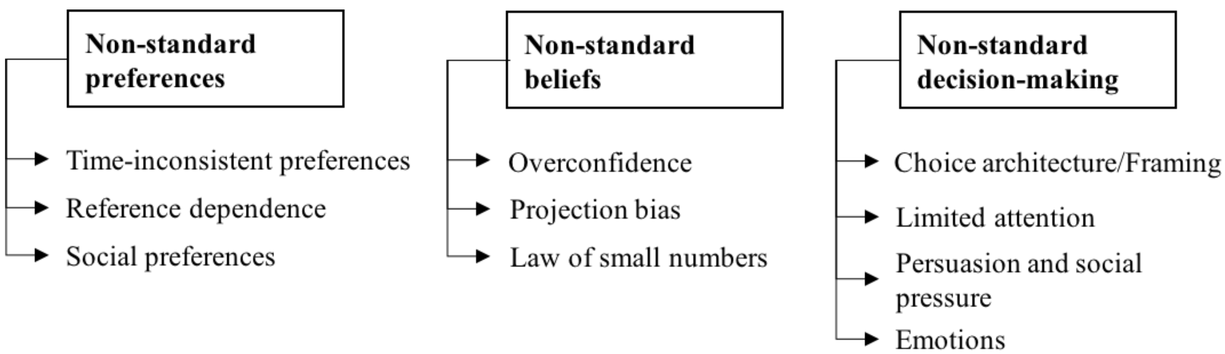

Figure 1: Three classes of behavioral biases

The first class of behavioral biases, non-standard preferences, refers to deviations from the assumptions of the standard model regarding the utility function (DellaVigna 2009; Rabin 2002). In the framework of intertemporal choice, the rational decision-maker has time-consistent preferences, which are modeled using exponential discounting of future utility. This implies that, for example, if someone chooses one apple today over two apples tomorrow, the same choice should hold at any other point in time, i.e., one apple in a year should be preferred to two apples in a year and one day. Thaler (1981) has provided experimental evidence that in such cases, preferences might, in fact, reverse so that two apples in a year and one day would be preferred to an apple in a year. This implies time-inconsistent preferences and discount factors, such that the outcomes of the near future are discounted more steeply than the outcomes of the distant future. Such discounting behavior is generally modeled by a (quasi-) hyperbolic discounting function (Laibson 1997; Loewenstein and Prelec 1992) and has been termed “present bias”, “hyperbolic discounting” or “declining impatience” (Urminsky and Zauberman 2016). Moreover, this concept can capture consumers’ problems of self-control. For example, suppose a person signs up for a gym membership to force their future self to exercise more. As the future gets closer, e.g., the person must decide whether to exercise today, the future utility is discounted more steeply, so the person tends to procrastinate and postpone exercising (DellaVigna and Malmendier 2006).

Kahneman and Tversky (1979) provided evidence of the violation of one of the of the standard model's core assumptions, namely that a rational agent maximizes a global utility function. This assumption entails that valuation is based on overall wealth. Instead, Kahneman and Tversky (1979) propose that the utility function is defined relative to a reference point (reference dependence). The reference point defines what is considered a gain and what is considered a loss by the decision-maker. To capture diminishing sensitivity, the gain function is assumed to be concave, while the loss function is convex. Reference dependence has become one of the main building blocks of prospect theory; additionally, to accommodate the empirical evidence suggesting that people are more sensitive to losses than to gains (loss aversion), prospect theory assumes a steeper value function for losses. While prospect theory stems from evidence generated in the context of risky choice, these two key features – reference dependence and loss aversion – can explain, for example, the endowment effect, which refers to the finding that the mere possession of an object induces individuals to value it more than they did before possessing it. The endowment effect serves as a primary explanation for the observed asymmetry in exchanging goods with or without initial possession (Knetsch 1989), as well as for the so-called willingness-to-pay and willingness-to-accept asymmetry (Kahneman, Knetsch, and Thaler 1991; Knetsch 1989). In the context of risky choice, the third key assumption of prospect theory concerns the non-linear probability weighting function. This assumption aims to capture the early evidence by Allais (1953) that people tend to overweight small probabilities and underweight large probabilities (known as "Allais's paradox" or "common ratio violation").

Furthermore, the standard model is built on the premise that the individual value function depends only on own payoffs and does not account for other-regarding preferences such as social preferences. Vast empirical evidence, however, suggests that people are not purely self-interested but rather involved in charitable giving (DellaVigna, List, and Malmendier 2012) and concerned with social welfare and fairness, e.g., in ultimatum or dictatorship games (Camerer and Thaler 1995, 1995, 1995; Fehr and Gächter 2000, 2000). Also relevant in this context are social- and self-image effects, where rewards (whether material or image-related) for prosocial behavior can even be counterproductive (Benabou and Tirole 2006).

The second class of deviations, non-standard beliefs, builds on the empirical evidence suggesting that consumers form systematically incorrect beliefs and do not act as Bayesian information processors (DellaVigna 2009; Rabin 2002). Three major causes can come into play in this context. First, belief-based biases might be due to overconfidence, which might take different forms, including systematic over- or under-estimation of own capabilities and knowledge, as well as overprecision, i.e., the degree of certainty in one's own beliefs, predictions and capabilities (Windschitl and O'Rourke 2015). Moreover, consumers tend to project their current preferences into future states, which is known as projection bias (Loewenstein 1996; Loewenstein, O'Donoghue, and Rabin 2003). This bias may come into play, for example, when ordering or buying food in a hungry state (Read and van Leeuwen 1998) or ordering winter clothing on an unusually cold day (Conlin, O'Donoghue, and Vogelsang 2007). Another source of belief-based biases is the misconception that small random samples are as representative as large samples, known as the law of small numbers (Tversky and Kahneman 1971). One such example is the so-called gambler's fallacy, that belief that, for example, after several occurrences of heads in a coin toss, tails will occur next to somehow restore the balance (Tversky 1974). A related misconception is the so-called "hot hand fallacy", where subjects tend to believe that positive correlation exists in random processes, i.e., after a sequence of heads in a coin toss, another head is more likely to occur (Gilovich, Vallone, and Tversky 1985).

The third class of deviations, which DellaVigna (2009) refers to as non-standard decision-making, addresses violations of the assumption of utility maximization. Rationality assumptions imply that choices are not affected by the environment/context or by the way the options are presented to the decision-maker. Research has shown, however, that the particular choice architecture does indeed affect the choices people make (Thaler, Sunstein, and Balz 2013). Specifically, we will discuss framing effects and local context effects. A number of experimental studies have shown the robustness of framing effects, i.e., when logically but not transparently equivalent problem formulation affects individuals' choices (Rabin 1998). While in some cases, framing effects may arise due to a reference-dependent utility function, in other cases, such effects might affect preferences by making certain characteristics of options more salient. Putting aside the potential explanation for the existence of framing effects, they result in suboptimal choices from the perspective of the utility maximization assumption. Levin, Schneider, and Gaeth (1998) further outline that framing might implicitly manipulate goals. For example, Meyerowitz and Chaiken (1987) show that women are more likely to conduct a breast self-examination when the negative consequences are stressed. Moreover, in an intertemporal context, Loewenstein (1988) shows that, keeping the time interval constant, describing the same option as a delayed or expedited decision results in different discount rates, which violates the assumptions of rationality. This phenomenon is referred to as "temporal framing" or "delay-expedite asymmetry". Furthermore, choices might be affected by a particular composition of the choice set, resulting in non-utility-maximizing behavior (Simonson and Tversky 1992). These types of effects are accordingly named context effects and include compromise, attraction, and similarity effects, which violate the independence of irrelevant alternatives, regularity, and betweenness inequality assumptions of the standard model. The compromise effect (also known as "extremeness aversion") describes a situation in which a product attracts a larger share in a setting where it is a middle rather than an extreme option (e.g., Simonson 1989; Simonson and Tversky 1992). The attraction effect (also known as "asymmetric dominance" or the "decoy effect") implies that adding an asymmetrically dominated alternative to a choice set can lead to an increase in the probability of choosing the alternative that dominates it (Huber, Payne, and Puto 1982; Huber and Puto 1983). Tversky (1972) further distinguishes the similarity effect: An alternative loses more choice share to another more similar alternative.

Furthermore, the standard model operates under the strict assumption that individuals consider all available information in their decision-making. This premise, however, has attracted criticism since Simon (1955), who suggested that individuals operate under bounded rationality and tend to simplify complex decisions. Limited attention, which might manifest as over- or underweighting, or completely ignoring some of the information available at no (or very low) cost, can result in suboptimal decisions from the perspective of the standard model.

The normative theory further assumes that rational agents would be wary of the incentives that the provider of the information (e.g., firms, politicians, etc.) has and would account for this when making decisions. The literature on the effects of persuasion, however, shows that this is not necessarily the case, and quite often the beliefs of the information provider might, in fact, have excessive influence on individuals' attitudes and behavior (DellaVigna 2009). As DeMarzo, Vayanos, and Zwiebel (2003) argue, this is an important bias, which offers a simple explanation for the existence of such phenomena as propaganda. Moreover, individuals' attitudes and behavior might be subject to social pressure (DellaVigna, List, and Malmendier 2012), i.e., subject to explicit pressure from their reference group (e.g., peers, family, etc.).

In addition, the rational agent is considered to be deliberate and emotionless. Emotions, however, including visceral influences, e.g., hunger or thirst (Loewenstein 1996); anticipatory emotions, e.g., anxiety or fear; as well as anticipated emotions, e.g., regret (Loewenstein et al. 2001), have been shown to drive consumer behavior.

While we largely follow DellaVigna (2009) in separating the three classes of deviations, it is important to note that quite often, these are interrelated. For example, persuasion might result in nonstandard decision-making through the induced biased beliefs. Furthermore, emotions may act as mediators of some of the other biases, e.g., self-control problems, social preferences (DellaVigna 2009) and attitudes towards risk (Loewenstein et al. 2001).

2.2. Marketing Mix Instruments

To provide marketing managers and researchers with a deeper understanding of the previously mentioned biases in a marketing context, we adopt an instrumental view. Marketing is an exchange relationship between customers and firms, where, in order to reach their goals, firms use the marketing mix instruments (Iacobucci 2017; Kotler and Keller 2012; Winer and Dhar 2014). We structure our literature review based on these instruments and employ the classical definition of the 4Ps – product, price, place, and promotion – as suggested by Jerome McCarthy in 1960 (McCarthy and Perreault 2002) and covered in numerous marketing textbooks (Iacobucci 2017; Kotler and Keller 2012; Winer and Dhar 2014). Product refers to any tangible or intangible item that satisfies particular consumer wants or needs. We consider such components as product variety (e.g., product line); product features, quality, and brand; as well as warranties and product returns. With regard to Price, i.e., the amount that a consumer pays for a product (including recurring payments, multi-part tariffs, and renting), we include, for example, list price and discounts. Under Place, we consider channels (online and offline) through which the products are marketed to consumers, (retailer) assortment decisions, location, and (in-store) placement. Promotion includes communication activities that aim at directly or indirectly informing, reminding as well as persuading consumers about the firm’s products (Kotler and Keller 2012). In our case, this includes advertising (at the point of sales (POS) and other media), direct marketing, and sales force.

3. Behavioral Biases in Marketing

In this section, we present, for each marketing instrument, selected marketing papers that cover specific deviations from the standard model, grouped by the three classes of deviations from the neoclassical assumptions mentioned in the previous section. We selected these papers based on relevance, journal quality, citations, and recency. Table 1 gives an overview of the behavioral biases and marketing topics that we discuss in the following (see Table A in the appendix for the corresponding references).

Marketing Instrument	**Group of Biases**	**Bias**	**Marketing Topic**
Product	Non-standard preferences	Time-inconsistent preferences	• Utilitarian vs. hedonic product choice • Durable product adoption
		Reference dependence	• Extended warranties • Product insurance • Endowment effect • Return policy
		Social preferences	• Fair trade labeling
	Non-standard beliefs	Overconfidence	• New product adoption
		Projection Bias	• Remote purchases • Durable goods purchases
		Law of small numbers	• Investment decisions
	Non-standard decision making	Choice architecture/Framing	• Package labeling • Delivery option • Local choice context • Preference for "all average" • Product line design
		Limited attention	• Information overload • Consideration/choice set construction • Inattention to attributes • Left-digit bias
		Persuasion and social pressure	• Peer effects
		Emotions	• Branding
Price	Non-standard preferences	Time-inconsistent preferences	• Quantity discounts • Consumption impulses
		Reference dependence	• Reference prices • Price sensitivity • Price-quality heuristic
		Social preferences	• Pay What You Want • Charitable giving • Price fairness
	Non-standard beliefs	Overconfidence	• Tariff choice
		Projection Bias	• Usage prediction • Habit formation
		Law of small numbers	• Store image
	Non-standard decision making	Choice architecture/Framing	• Price presentation • Price promotion

			• Partitioned prices
		Limited attention	• Price knowledge
		Persuasion and social pressure	-
		Emotions	• Bidding behavior
Place	Non-standard preferences	Time-inconsistent preferences	• Impulse buying
		Reference dependence	• Endowment effect • Need for touch
		Social preferences	-
	Non-standard beliefs	Overconfidence	• Online search
		Projection Bias	-
		Law of small numbers	-
	Non-standard decision making	Choice architecture/Framing	• In-store marketing • Store layout • Recommendations • Search cost • Ranking effects • Channel effects
		Limited attention	-
		Persuasion and social pressure	• Social influence
		Emotions	-
Promotion	Non-standard preferences	Time-inconsistent preferences	• Sweepstakes and lotteries • Hedonic consumption
		Reference dependence	• Probabilistic rewards • Frequency (loyalty) programs • Reward structure of sweepstakes
		Social preferences	• Charitable giving • Direct marketing • Sales force incentives
	Non-standard beliefs	Overconfidence	• Probabilistic promotion • Delayed promotion • Redemption slippage
		Projection Bias	-
		Law of small numbers	• Casino gambling
	Non-standard decision-making	Choice architecture/Framing	• Redemption rates • Comparative advertising
		Limited attention	• Feature advertisement
		Persuasion and social pressure	• Exaggerated claims • Anecdotal claims
		Emotions	-

Table 1: Overview of Behavioral Biases and Marketing Keywords

3.1. Product

3.1.1. Product & Non-Standard Preferences

Present-biased preferences are of particular interest in decisions involving (1) the choice between utilitarian vs. hedonic products in settings when a time lag exists between ordering and consumption of such products and (2) durable product adoption, where the adoption decision depends not only on the person's static preferences but also on how and how much they discount future utility. In the first case, Milkman, Rogers, and Bazerman (2009; 2010) find that while products with more utilitarian or "should" characteristics are preferred at the time of ordering in advance, preferences switch to products with more hedonic or "want" characteristics at the time of consumption in the context of movies and groceries. Such preference reversals are consistent with present-bias preferences and can potentially be explained by self-control, as when ordering in advance, people might choose more "should" options to control their impulsive future selves. Similar to the example of cigarettes in the study by Wertenbroch (1998) discussed in section 3.2.1., such behavior is inconsistent with standard rationality assumptions of time consistent preferences. Regarding present-bias in the context of durable goods adoption, Dubé, Hitsch, and Jindal (2014) explore the susceptibility of consumers to this preference-based bias using the example of Blu-ray players. First, they develop a new experimental design that elicits product adoption choices conditional on expert predictions of future market conditions (e.g., prices), which enables the joint identification of utility and discount functions. Second, they test, in two choice experiments, different assumptions regarding the discounting behavior. In particular, they test (quasi-)hyperbolic discounting against the geometric discounting of the standard model, simultaneously accounting for heterogeneity in the discounting rates of consumers. They find that the dynamic choice model allowing for present-bias does fit the data slightly better in one experiment. However, the distribution of the individual estimates for the present-bias is concentrated at one, suggesting only limited empirical support for hyperbolic discounting. The small share of individuals who do exhibit present-bias, however, and subsequently act in contrast to the standard assumptions of time-consistent preferences, would be more prone to earlier product adoption.

Regarding reference-dependent preferences, Wood (2001) provides experimental evidence that in remote purchase environments (e.g., catalog sales, online retailing), under a more flexible return policy (full refund vs. no refund for shipping costs), total deliberation time (over two stages of the decision-making, initial ordering and keep-or-return decision after delivery) decreases and simultaneously increases the product quality perception. Moreover, they establish that respondents under a more flexible return policy are also less keen on continuing the search, which is counterintuitive. As the authors suggest, such a result can be explained by the endowment effect. After the initial purchase, the consumer is in possession of the product, which shifts the reference point so that returning the product would imply occurring losses. Wang (2009) provides further support for the endowment effect in product returns in the context of “in-store” environments. Manipulating the return deadline, the author finds that more flexible policies increase the net purchase rate. Flexible return policies induce people to put less thought into the buying (ordering) decision, as returning the product is easy, and therefore a more informed decision can be made later at the keep-or-return stage. Thus, in the absence of the endowment effect (i.e., under the standard model), one would expect an increase in deliberation time at the keep-or-return stage. In the presence of the endowment effect, however, due to mere possession, the valuation of the product seems to be higher, and deliberation at the keep-and-return stage does not increase.

Furthermore, in practice, we can observe that many consumers pay high premia for extended product warranties and other types of insurance, which would imply an unrealistically high degree of risk aversion. However, in describing such behavior, it is not clear what the primary driver of risk attitude is: risk aversion (diminishing returns in utility), loss aversion (which requires a reference-dependent utility function), or nonlinear probability weighting. Jindal (2015), for example, finds that loss aversion is the most important of the three abovementioned drivers in the context of extended warranty choices for washing machines. This finding is robust across two different mechanisms, simultaneous choice – when the product and warranty choice is a joint decision – as well as sequential choice – when consumers first decide whether to buy the product and then decide whether to purchase an extended warranty. From a firm’s point of view, this is a problem of bundling or unbundling the product and the warranty. The author uses a flexible modeling approach that distinguishes among all three potential drivers of risk attitudes and simultaneously accounts for heterogeneity in all model components. Furthermore, an innovative survey design is used to attenuate possible belief-based biases: respondents choose products and warranties under given failure probabilities. Jindal (2015) shows in simulations (based on the estimated models) that not accounting for risk aversion, loss aversion, and nonlinear probability weighting leads to roughly 16-20% lower optimal prices and, consequently, reduced profits for manufacturers.

Lastly, in the context of products, social preferences might come into play for product features such as fair trade labels. Hainmueller, Hiscox, and Sequeira (2015) provide more recent empirical evidence from a large-scale field experiment in which sales for (whole and ground) coffee increased by approximately 8% when the product carried a fair trade label. A fair trade label does not improve the quality of the product itself (i.e., there is no difference in taste for a fair trade food product compared to the same one without a label), yet there is ample empirical evidence from surveys that consumers are willing to pay more for socially responsible products (see Tully and Winer 2014for a meta study). This implies that consumers perceive higher utility for products with fair trade labels because they care about others (i.e., the workers), indicating social preferences that would not matter in the standard model.

3.1.2. Product & Non-standard Beliefs

Overconfidence can play a crucial role in product choice, particularly for new product adoption. Here, consumers need to predict and anticipate the utility of new products that have features they can hardly evaluate without experiencing them (Guo 2006). Consumers can be overly optimistic regarding the future usefulness of capabilities and then fail to use the features they paid for. Meyer, Zhao, and Han (2008) provide empirical evidence from experiments on such valuation-usage disparity: respondents are willing to pay for a new set of controls in a computer game, but after ownership, usage is rather limited. While hyperbolic discounting can potentially explain this phenomenon, as individuals procrastinate learning the new capabilities of the product, belief-based biases such as overoptimism might act as a further driver. The latter is a bias closely related to overconfidence, where decision-makers are overly positive about the prospect of something desirable. In this particular context, the valuation-usage disparity can be a result of individuals being overoptimistic about the likely performance value of the new set of controls.

The product choices of consumers might also be influenced by projection bias. This is especially true for goods that are purchased for later consumption (e.g., catalog/internet purchases) or durable goods (Conlin, O'Donoghue, and Vogelsang 2007). Here, consumers have to forecast how much utility they will derive in the future, and this carries the risk that they only project their current preferences into the future. Busse et al. (2015) analyze automobile purchases and investigate whether specific product choices are affected by belief-based biases, such as the projection bias. Indeed, they find that the weather has an impact and that convertibles (four-wheel-drive cars) have higher sales if the weather is warm (cold) at the time of purchase. Busse et al. (2012) also report similar findings for the housing market, where consumers tend to buy houses with swimming pools in the case of warm weather at the time of purchase.

Next to projection bias, two product-related belief-based biases, which stem from the law of small numbers, are the gambler's fallacy and the hot hand myth. Both biases are well documented in marketing, particularly in the context of trading decisions of consumers at the stock market. Johnson, Tellis, and Macinnis (2005) conduct an experiment where respondents have to choose one out of two products (i.e., stock) which differ in their past performance. Under the standard model, past random events should not have an influence on current decisions. However, which bias (hot hand vs. gambler's fallacy) dominates depends on whether one wants to buy or sell a stock and on the length of the trend in the available information. In the buying condition, the hot hand fallacy dominates ("buy a winner") as the length of the trend increases. Only a minor share of respondents would "buy a loser," hoping the trend will reverse. However, in the selling condition, the picture is less clear. A considerable share of respondents would sell a winning stock because they anticipate that the trend will reverse. This effect is strongest for a trend of medium length.

3.1.3. Product & Non-Standard Decision-Making

Product choices might be affected by the framing of attribute information. Ample evidence suggests that positive vs. negative frames affect choices. Hence, regarding product attribute information, it might matter how certain information is described, e.g., on a package. Levin and Gaeth (1988) find that describing ground beef as "75% lean" vs. "25% fat" increases the favorability of a consumer's evaluation of the product. This contradicts standard rational decision-making, as both descriptions report exactly the same information, only differently. A rational consumer would not have been susceptible to such framing effects and would have evaluated the products under each description as equally favorable.

Temporal framing (i.e., delay-expedite asymmetry) is of particular interest in marketing in the context of remote purchase environments. For example, online retailers offer different delivery options for the same product (e.g., same-day delivery, next-day delivery, etc.). Loewenstein (1988) provides evidence that consumers have overall higher discount rates when delaying an outcome rather than expediting it, a robust deviation from a normative discounting utility model. Malkoc and Zauberman (2006) provide experimental evidence of this effect in a marketing context that mimics DVD purchases on Amazon. In particular, they show that in a delay frame, consumers require higher compensation (e.g., larger price discounts) to wait longer (e.g., choosing a later date over same-day delivery) compared to the price they are willing to pay for getting the product earlier (expedite frame). Furthermore, they find that the pattern of discounting can differ depending on the temporal frame, such that consumers demonstrate the greater extent of present-bias (i.e., a steeper discounting) when delaying the delivery compared to expediting it.

Choosing a product from a set of alternatives implies trading off different attributes of the products (e.g., quality, brand, packaging, price, etc.). In such situations, consumers might be susceptible to context effects, resulting in choices that are not consistent with standard decision-making. Many studies in the marketing literature have shown the robustness of these phenomena across a wide range of product categories, particularly in settings involving the choice between three alternatives varying on two attributes (e.g., Dhar, Nowlis, and Sherman 2000; Dhar and Simonson 2003; Simonson 1989). For example, Kivetz, Netzer, and Srinivasan (2004) find empirical evidence for the compromise effect. In particular, they analyze consumer choices in two product categories, which are described on two attributes: portable PCs varying in speed and memory as well as speakers varying in power and price. They find that consumers do indeed prefer the middle option, which provides a good trade-off on both dimensions. Furthermore, testing different models that allow capturing the compromise effect, they show that such models, in general, provide a better fit and higher predictive validity compared to the standard model operating under rationality assumptions. However, in the particular applications they use, it is difficult to determine the exact mechanism creating the compromise effect.

Rooderkerk, van Heerde, and Bijmolt (2011) analyze the choice of digital cameras, which are described using their picture quality (in megapixels) and optical zoom. Following Tversky and Simonson (1993), they propose an approach that accommodates not only the compromise effect but all three context effects. In particular, they suggest separating the total utility into context-independent and -dependent parts, modeling the latter as a linear combination of compromise, attraction, and similarity effects. This allows all three effects to co-occur, which is indeed the case in their empirical application. The model outperforms the traditional random utility model. Most importantly, the authors demonstrate that even after accounting for preference heterogeneity, context effects still prevail, excluding preference heterogeneity as a possible explanation of the observed context effects on the aggregate level, as described in the literature. The specific drivers and causes of context effects still require further investigation. For example, Kivetz, Netzer, and Srinivasan (2004) suggest that complexity can potentially attenuate the magnitude of the compromise effect, and Dhar and Simonson (2003) outline a no-choice option (i.e., whether the consumer is forced to choose or not) as a potential moderator of context effects.

The consequences of limited attention have also been given a rather prominent position in the marketing literature. Substantial evidence suggests that increasing the number of alternatives or attributes of the choice setting leads to information overload (Malhotra 1982), which can prompt decision-makers to apply heuristic strategies and ignore information (Payne et al. 1992). This, in turn, results in suboptimal choices from the standpoint of the standard model. In particular, consumers may limit their attention to a subset of alternatives or attributes. For example, in the context of powder detergent brand choice, Bronnenberg and Vanhonacker (1996) show that 62% of loyal consumers consider only one brand, and 60% of more sensitive consumers consider 2-3 brands in their choice set. Gilbride, Allenby, and Brazell (2006) focus on inattention to attributes and, based on a choice experiment, provide evidence that consumers consider only approximately 46% of attributes in their decision-making. Such results contradict standard decision-making, as inattention to attributes or alternatives results in non-compensatory decision rules. From the modeling perspective, not accounting for the fact that individuals might consider only subsets of attributes or alternatives in their decision-making results in biased estimates and false insights derived from the estimated parameters, such as willingness-to-pay measures or the relative importance of attributes (Gilbride, Allenby, and Brazell 2006), as well as competitive dynamics and substitution of brands (Bronnenberg and Vanhonacker 1996). To better understand the underlying mechanisms of inattention, it is important to relate inattention to potential drivers, such as complexity measures (Swait, Popa, and Wang 2016).

Inattention can further result in incomplete processing of the information provided by a specific attribute. One of the main examples is the left-digit bias – the tendency to ignore the rightmost digits of numeric information. This is relevant in the context of product features, which are described quantitatively (e.g., power, weight, and price; see Koschate-Fischer and Wüllner (2016) for an overview). Lacetera, Pope, and Sydnor (2012) find strong evidence of left-digit bias in the processing of the mileage of used cars, which results in discontinuity of sales prices. This is a surprising result, as buying a used car is still costly, and the mileage itself is an important and readily available piece of information when making a decision.

The marketing literature has also contributed to the research on social influence or peer effects. For example, Narayan, Rao, and Saunders (2011) conduct an experiment with MBA students in which they analyze the choices in E-book readers. In the first stage, the students participate in a typical discrete choice experiment stating their preferred products. In the second stage, the experiment is repeated, but the respondents are informed about the choices of their peers during stage one. The authors observe that the choices change in the second round, so that strong brands obtain an even larger choice share, while the weak brands' choice share decreases. Such behavior is strongly consistent with peer effects, as respondents tend to conform with the preferences of their respective reference group, resulting in non-utility-maximizing behavior. However, the authors find that the number of influencers has a positive but diminishing moderating effect on peer influence.

Lastly, emotions have also been shown to affect the product choice decisions of consumers. Brands are valuable intangible assets of firms that strongly influence consumer choice and lead to vertical product differentiation (Keller and Lehmann 2006). However, emotions, and particularly negative emotions, play a significant role in the relationship of consumers with brands. Romani, Grappi, and Dalli (2012) develop and test a new scale with six distinct brand-related emotions (i.e., anger, discontent, dislike, embarrassment, sadness, and worry). Their study shows that negative emotions towards a brand also influence consumer decision-making. Consumers who feel, e.g., dislike, anger, or sadness towards a brand, have a higher likelihood of complaining about the brand, engaging in negative word of mouth about the brand, and switching to a competing brand. Under rationality assumptions, consumer behavior, by definition, should not be influenced by general or brand-related emotions. Therefore, such findings argue for "irrationality" in a narrowly defined sense.

3.2. Price

3.2.1. Price & Non-standard Preferences

Using multiple methods and data sources, Wertenbroch (1998) studies consumption self-control in the context of relative "vice" (i.e., regular) and "virtue" (e.g., reduced fat, calorie, or caffeine) goods. He shows that to control their unwanted consumption impulses, consumers voluntarily and strategically ration the quantities of goods they purchase; thus, they buy smaller quantities at a higher per-unit price. For example, regular smokers often buy their cigarettes by the pack, although they could afford to buy 10-pack cartons. In this way, they give up per-unit savings from quantity discounts and increase their transaction costs to make smoking overly costly for themselves. Such behavior might seem intuitive but is inconsistent with the time consistency of preferences assumed by the standard model. As a consequence, vice consumers are less likely than virtue consumers to buy larger quantities in response to unit price reductions such as quantity discounts.

Reference dependence in the context of pricing is a widely researched area in the marketing literature, which we illustrate through examples from reference price theory, loss aversion, and the price-quality heuristic. Various studies in the pricing literature use prospect theory (Kahneman and Tversky 1979), especially its features of reference dependence and loss aversion, as a conceptual framework for their analyses; these studies use the applications and boundaries of prospect theory to answer marketing research questions. One of the most prevalent phenomena studied in this context is reference price theory. Kalyanaram and Winer (1995) establish three generalizations from reference price research that are drawn from broad empirical research in marketing. The first and the third are more general in that they also apply to other contexts of reference dependence, whereas the second generalization is specific to pricing research. The first generalization states that reference prices have a consistent and significant impact on consumer demand. Typically, the reference price is the "perceived" or expected price. The third generalization states that consumers react differently to price increases and decreases relative to the reference price, namely they react more strongly to price increases (Kalyanaram and Winer 1995). In general, consumers perceive prices above the reference price as losses and prices below the reference price as gains. Finally, the second generalization implies that "internal" reference prices use past prices as part of the consumer's information set. This generalization aims at the question of how reference prices are formed. There is convincing empirical evidence that past prices play an important role in the reference price formation process. For a more comprehensive assessment of reference price research, see also Mazumdar, Raj, and Sinha (2005). In general, reference price theory clearly deviates from the standard model, in which agents make decisions based on actual prices and income. Conversely, reference price theory assumes that consumers also base their decisions on perceived prices – namely the reference price, which serves as an internal standard against which observed prices are compared.

Returning to loss aversion, early research found loss aversion to be ubiquitous, whereas more recent research stresses the importance of also considering its boundaries and attenuations (e.g., Novemsky and Kahneman 2005). For example, Bell and Lattin (2000) show that loss aversion is not a universal phenomenon but that accounting for price-response heterogeneity leads to lower and frequently non-significant estimates of loss aversion, at least in the context of frequently purchased grocery products. They argue that the kinked value function, as implied by loss aversion, is confounded with the slopes of the response curves across consumer segments with different price responsiveness. A more price sensitive consumer is assumed to have a lower reference point and thereby encounters more prices above his reference point (i.e., the response curve is steeper for losses). Analogously, less price-sensitive consumers have less-steep curves in the domain of gains. Therefore, cross-sectional estimates of loss aversion that do not account for heterogeneity in price responsiveness will be biased upwards.

Finally, reference dependence can also help explain the so-called “price-quality” heuristic, which represents the fact that consumers often use price as a proxy for quality, resulting in a positive correlation between price and product liking. According to (Gneezy, Gneezy, and Lauga 2014), expectations are an important driver of the price-quality relationship. High prices increase expectations, which serve as a reference point against which people evaluate their consumption experience. If the consumption experience meets or exceeds this reference point, the traditional price-quality effect is observed. However, when the price is high and quality is relatively low, the product falls short of the consumer’s reference point, and the price-quality relationship is reversed. As a result, consumers evaluate a low-quality product with a high price more negatively than a low-quality product with a low price.

Pay What You Want (PWYW) is a pricing mechanism in which consumers make voluntary payments for a good or service for private as well as public consumption (Spann et al. 2017). Although a niche mechanism, many examples of sellers applying PWYW can be found in various industries, such as the music industry, gastronomy, or entertainment (Krämer et al. 2017). Much research focuses on the behavioral drivers that influence payments. Schmidt, Spann, and Zeithammer (2014) show that outcome-based social preferences and strategic considerations to keep a seller in the market can explain why and how much buyers voluntarily pay to a PWYW seller. This behavior clearly deviates from the standard model, as purely self-interested and myopic consumers, for whom utility only depends on their own payoff, would simply pay nothing (DellaVigna 2009). Jung et al. (2017) extend the phenomenon of voluntary payments to shared social responsibility, i.e., whether a charitable contribution is made with a purchase. Their study shows that consumers are sensitive to whether any part of their payment goes to charity but largely insensitive to the amount of that payment.

With regard to perceived price unfairness, Campbell (1999) shows that consumers are less likely to conduct business with a firm that is perceived to have established unfair prices. In terms of price increases, the study demonstrates that consumers' inferred motive for the price increase and the relative profit to be made by the firm because of the increase both affect consumers' perceived price fairness. For example, when participants concluded that a firm had a negative motive (e.g., increasing profits) for the price increase, the increase was perceived as less fair than when the firm had a positive motive (e.g., donating additional profits to charity). Moreover, firm reputation moderates the effect of inferred relative profit on inferred motive. Consumers are more willing to give a firm with a good reputation the benefit of the doubt when speculating about the inferred motive for the price increase. This phenomenon again contradicts standard economic theory, as the motives behind firms' pricing strategies should not affect their customers' decision-making. However, Campbell's (1999) study shows that consumers also take the interest of the firm into account, consistent with the example of customer-driven pricing mechanisms discussed above.

3.2.2. Price & Non-standard Beliefs

Focusing on the internet service industry, Lambrecht and Skiera (2006) find that consumers make "mistakes" in tariff choice in that they often do not pick the tariff that is financially optimal for them. The authors show that many consumers pick the flat-rate tariff even when it is not the least costly choice (i.e., "flat-rate bias"), and a smaller share of consumers picks the pay-per-use tariff, although they would save money under the flat-rate tariff (i.e., "pay-per-use bias"). With regard to the causes of these biases, the study shows that overestimation of usage leads to a flat-rate bias and that underestimation of usage leads to a pay-per-use bias. In addition, they show that consumers seem to derive additional benefits from the flat-rate option, and these benefits also influence tariff choice. The so-called insurance effect (reliability of the billing rate) and the taxi meter effect (the joy and independence of using a flat-rate) are also correlated with the flat-rate bias. Although not explicitly mentioned in the study, overconfidence is a leading candidate explanation for mistakes being made in tariff choice, as proposed by other related studies (DellaVigna and Malmendier 2006; Grubb 2012). More specifically, it is likely that overconfident consumers overestimate their ability to predict their future demand and its precision; thus, they misestimate their demand, which leads to mistakes in tariff choice. Recall that under the assumptions of the standard model, consumers should form rational expectations, and these expectations should be valid, on average.

Returning to the previous example of self-control in the context of cigarette consumption, we discussed how overconfident consumers might overestimate their ability to forecast their future demand and thereby misestimate it. While they might underestimate their demand for vice goods, they might overestimate their demand for virtue goods. Acland and Levy (2015) study such a virtue good by analyzing, in a field experiment, the influence of incentive intervention on gym attendance. They incentivized the treatment group with $100 if they visited the gym twice a week during one month. In addition, they provided subjects with coupons that subsidized each gym visit during an indicated week. Their results show that consumers overpredict future attendance, which they attribute to consumers having a naïve present bias, such that consumers fail to predict the future impact of immediate gratification in the form of a price discount on gym attendance. In addition, the study finds an increase in the treated gym members' attendance after the treatment phase (although only for a short period of time), which they attribute to habit formation. Participants, however, did not predict such an increase in gym attendance after the treatment phase. The authors' explanation for this phenomenon is projection bias with regard to habit formation, as participants did not expect the increased attendance in the treatment phase to result in a habit that would also increase their attendance in the immediate post-treatment period. Instead, participants exhibited incorrect beliefs in line with the projection bias, as they expected their future preferences regarding gym attendance to remain the same as the present ones.

Next to overconfidence and projection bias, the law of small numbers is documented in marketing research. For example, it could be shown that consumers seem to generalize from a small sample of advertised prices to the overall store price image (Cox and Cox 1990). Using an experiment, the authors analyze the effect of different versions of retail advertisements – with differing price and product representations – on the perceived store's overall price level. The results show that when advertised prices are displayed as reductions from a previous higher price, consumers perceive the store to have overall lower prices. Thus, consumers generalize from a small and possibly highly selective sample of advertised reference prices to make inferences about the population of prices in the entire store. This illustrates the law of small numbers, as information on a small sample is overweighed, and consequently, consumers' decisions are likely to be biased.

3.2.3. Price & Non-standard Decision-Making

Price framing is a widely researched area in the marketing literature. Many features of how a price is communicated to consumers – for example, whether it is accompanied by a reference price – significantly influence price perceptions. In their meta-analysis, Krishna et al. (2002) focus on experimental literature dealing with the impact of price presentation on perceived savings. Perceived savings is considered the main dependent variable because it is the most common method of measuring the reaction to price promotions (Krishna et al. 2002). Looking at how different price promotion characteristics affect perceived savings, it was shown that higher values for both percentage of savings and absolute savings increase perceived savings, but percentage has a larger effect. This contradicts utility theory, which suggests that only the absolute dollar amount should have an effect on the evaluation of a price promotion. The effect of price promotion percentage is moderated by store type, that is, whether the promotion is by a department store, whether the regular price is used as an external reference price, and by tensile claims (e.g., savings of __% and more). Moreover, price presentation effects also play an important role when measuring the effect on perceived savings. For example, large effects within this category are caused by whether a sale was announced, the promotion plausibility, tensile claims, within-store frames (e.g., our current price is x, our regular price is y), and external reference prices. To give an example, tensile claims are perceived as lower savings than other non-tensile (objective) claims (e.g., savings given as a coupon), as the low end of the price promotion is highlighted in tensile claims. Finally, situational effects seem to be less important than price promotion characteristics and price presentation effects in terms of effect size, but many of these effects are still very important for marketing managers. Brand type, store type, and type of good all have significant effects on perceived savings. With regard to store type, it was shown that sales in discount stores and department stores are perceived to be of lower value than sales in specialty stores, in supermarkets, and when the type of store was not mentioned (Krishna et al. 2002). All these examples clearly highlight that the context and the framing of a situation matter strongly for price presentation, promotions, and strategy. Prices framed differently were shown to have different effects on perceived savings or attitudes towards the price promotion or product.

Another example of framing that influences consumers' reactions to prices is partitioned prices – i.e., dividing a product's price into two mandatory parts, such as the base price of the product and a surcharge, for example, the shipping cost (Morwitz, Greenleaf, and Johnson 1998). Using experiments, the authors show that partitioned prices tend to decrease consumers' recalled total costs and to increase consumers' product demand in comparison with all-inclusive or combined prices. In line with the results above, the study also shows that the way in which the surcharge is presented also influences the reaction to partitioned prices. This is an indication of irrational behavior, as consumers should not differ in their demand depending on how the price is presented, as total costs remain the same.

Moving to limited attention, Dickson and Sawyer (1990) study price knowledge within the context of behavioral pricing in marketing. In their study, the authors employed personnel with clipboards who observed and interviewed shoppers in supermarkets. They observed shoppers at the point-of-sale and asked them questions regarding their price knowledge of items (e.g., the selling price or whether a product was on sale or not) that the shoppers had, just a moment before, placed in their shopping carts. The results show that only slightly more than half of the shoppers checked the price of the chosen item, and only slightly more than 20% also stated that they had checked the price of a competitor brand. Despite being interviewed directly after selecting the item, price recall accuracy was very low, as 21.1% of shoppers did not even give a price estimate, and only 47.1% of shoppers were able to report the exact correct price. These findings thus reveal that consumers do not make decisions using all the available (price) information there is, as predicted by the standard model, but pay only limited attention to price.

Finally, emotions were shown to influence decision-making in a pricing context. In order to illustrate this, Ding et al. (2005) analyzed emotions evoked in a Priceline-like reverse auction; specifically, they evoked the excitement of winning and the frustration of losing. Their study shows that the classic economic model, which predicts static bidding behavior in such a setting, did not capture the empirical bidding behavior, as bidders usually changed their bids after each round. Furthermore, the study shows that emotions strongly influence the bidding process and that emotions dynamically change as a function of the outcome of the previous bid. Thus, a bidder revises the bid every time his emotional state changes due to the outcome of the previous bid, thereby deviating from the rational benchmark model that predicts stable bidding.

3.3. Place

3.3.1. Place & Non-standard Preferences

In terms of self-control and place, we discuss self-control as a driver of impulse buying, as earlier studies have already shown that impulse buying is driven by – among other factors – distribution characteristics, such as the number of store outlets or prominent store displays (Stern 1962). With the diffusion of (additional) online channels, opportunities for impulse buying have increased, making it even more important to better understand the situational factors driving impulse buying (Vohs and Faber 2007). For example, the increased use of mobile devices (StatCounter 2016), which consumers typically carry around with them all day, offers marketers additional opportunities to increase impulse buying through in-app advertisements or mobile coupons. In their study, Vohs and Faber (2007) analyze how the depletion of resources that govern self-control affects impulse buying. Using three experiments, they manipulate self-regulatory resources and measure the effect on impulse buying. The results of the experiments show that participants whose resources were depleted 1) reported a higher willingness to pay for a series of items they were shown, 2) spent more time in a mock unanticipated buying situation, and 3) actually did spend more money in real purchase situations compared to the control group. Thus, this study illustrates how self-control problems can affect impulse buying behavior.

As computer usage has shifted from desktop computers to mobile phones and tablets (StatCounter 2016), interfaces have shifted towards touchpads and touchscreens (Brasel and Gips 2014). As consumers increase their e-commerce visits on touch devices, it is important to understand what impact touch has on consumer behavior. For example, Brasel and Gips' (2014) study analyzes the relationship between different touch interfaces and the endowment effect. The results from two online shopping scenarios show that touchscreens, as opposed to touchpads and mice, generate stronger psychological ownership, which increases the endowment effect and the willingness to accept for selected products. This behavior deviates from the standard model, as simply a change in the interface leads to an asymmetry in willingness to accept. The size of the endowment effects generated with different interfaces rival those conducted with real products, which shows that the endowment effect also occurs in online settings.

3.3.2. Place & Non-standard Beliefs

In this section, we combine findings from different studies to illustrate that when considered together, the findings indicate irrational consumer behavior. Because the Internet lowers search costs, one would assume that as a result, consumers are searching more online (Brynjolfsson and Smith 2000). However, as Johnson et al. (2004) show, consumers' searching on the Internet is relatively limited. The authors compare searches on competing e-commerce sites for three different product categories. On average, households only visit 1.2 book sites, 1.3 CD sites, and 1.8 travel sites during one month, reflecting very low levels of searching over all categories. Households with higher shopping activity tend to visit more sites, however, experience does not seem to increase the number of sites visited. There are no time-varying effects for books and CDs. Because travel constitutes a high-expenditure product, one would expect that experience might lead to more searching, but instead, search propensity slightly decreases over time. Such limited searching cannot be explained by efficient markets, as prices across these categories are significantly dispersed (Clemons, Hann, and Hitt 2002). Price observations for books and CDs from a similar study reveal that Internet retailer prices vary, on average, by 33% for books and 25% for CDs (Brynjolfsson and Smith 2000). Price differences are also apparent when comparing online and offline channels, as the authors find that prices on the Internet are 9-16% lower than prices in conventional stores (Brynjolfsson and Smith 2000). Although not explicitly mentioned in these studies, a likely explanation for too little searching is overconfidence. Consumers might overestimate the precision of their own information regarding prices and thereby underestimate the differences that might exist across different e-commerce sites, across online and offline channels, or over time. As a result, overconfident consumers tend to search too little.

3.3.3. Place & Non-standard Decision-Making

In a study on in-store marketing, Hui et al. (2013) analyze in-store travel distance and find that it affects unplanned spending. More specifically, they show how two different shopper marketing strategies – product category relocation and mobile coupons – can be used to increase in-store travel distance and thereby unplanned spending, as consumers are exposed to more in-store stimuli. Using simulations, they suggest that the relocation of three product categories (i.e., a form of physical framing) can increase unplanned spending by 7.2%. However, promoting three product categories via mobile coupons may increase unplanned spending by as much as 16.1% compared with the benchmark strategy of relocating product categories. As the two strategies are not mutually exclusive, the authors propose that both can be used simultaneously. The effectiveness of increasing travel distance through mobile coupons, and thereby increasing unplanned spending, is also confirmed by a follow-up field experiment. Here, the authors manipulate the proximity of the couponed category to the planned path (near vs. far), and they also manipulate the coupon amount. Again, the idea is that a coupon for an unplanned category that is farther away exposes the consumer to more in-store stimuli and thereby might lead to more unplanned buying. These predictions were confirmed, as the average amount in the far coupon group was much higher ($21.29) than in the near coupon group ($13.83). These results indicate that manipulations of the in-store travel distance clearly influence consumer behavior. One would expect rational agents not to deviate from their planned purchase behavior, regardless of the path they take in the store. However, as the study showed, the indirect manipulation of in-store travel distance led to more unplanned buying.

Whereas the previous study dealt with framing in a conventional store setting, the following study by Diehl (2005) shows how framing can have an effect on consumer behavior in the context of searching in online shopping. Whereas online environments are often assumed to offer lower search costs and the advantage of screening and sorting products (e.g., Alba et al. 1997), Diehl's (2005) study shows that the combination of orderings with lower search costs or more recommendations can lead to lower choice quality in terms of lower average quality of considered options and more attention to mediocre rather than better options from the considered set. Typically, screening tools in e-commerce sort through many options and recommend to consumers a list of products that fit a consumer's utility function best, ordered from best to worst. Because the best options are already listed at the top, additional search is unlikely to expose consumers to better options, as opposed to unordered environments. Thus, more searching in ordered environments exposes consumers to a lower average quality of inspected options, which can tempt consumers to choose lower-quality options. This aspect limits the benefits of ordered environments. Counterintuitively, this tendency to make lower quality choices is amplified if search costs are low and consumers are very motivated to be accurate in their searches, as they are encouraged to consider a broader range of products. That study shows – though doing so is not its main goal – how the framing of products in an online setting, realized through the ordering of products, can influence consumer choice. The presentation of the seemingly best option according to the utility function at the top of an ordered environment results in worse choices. For a similar study analyzing product search with recommendations, see also Dellaert and Häubl (2012).

Another question that arises when considering search in an online setting is how Internet browsing behavior differs between different online channels, i.e., personal computers and mobile phones. Ghose, Goldfarb, and Han (2013) empirically analyze search costs and geographic proximity (i.e., distance to store) on the mobile Internet vs. the PC-based Internet. They use rank as a measure of search cost, as consumers exhibit more cognitive and potentially physical effort when scrolling down a long list. Higher ranking effects suggest that it is more valuable to be ranked at the top. They expect ranking effects to be higher on mobile phones due to the comparably higher amount of scrolling down required on a small screen. In addition, because it is easier for mobile than PC users to go to nearby stores, the authors assume geographic proximity to be more important on a mobile phone. These predictions are confirmed using data from a South Korean microblogging website. First, the negative relationship between the rank and clicking on a post is larger for mobile phones. Moving one position upwards in the ranks leads to a 25% increase in the probability of clicking on that post for PC users and an increase of 37% for mobile users. Thus, the study shows that ranking effects are higher on the mobile Internet. Second, in terms of distance effects, preferences for geographically proximate brand stores are higher for mobile users. A one-mile decrease in distance between a user and a brand leads to an increase in the probability of clicking on that brand post of 12% for PC users and 23% for mobile users, showing that distance is more important for mobile users. Overall, the study shows how the framing of the search situation through different devices can influence consumer behavior, assuming that the same information is available across devices. In this context, framing is accomplished by the different devices used for product search – mobile vs. PC. More specifically, this study shows how, when framed through a certain device, attention is focused on different aspects of the options. One would expect rational consumers not to differ in their choices simply because different distribution channels are being used. However, the study showed how different channels led to differences in clicking behavior.

In this section, we have analyzed how framing can lead to non-standard decision-making. Next, we consider social pressure, more specifically social contagion and how it affects consumer behavior. Gardete (2015) studies social effects in the in-flight marketplace. This distribution channel is particularly suitable for the analysis of social effects, as the seating arrangements provide useful information on which passengers' activities can be seen by other passengers and because all purchases on the entertainment system are recorded with a time stamp. The results show that the purchase probability for a media item increases, on average, by 30% if a lateral neighbor (i.e., a neighbor next to the passenger in the same row) makes a purchase. The patterns that are revealed in the analyses cannot be sufficiently explained by classical social influence theories. For example, the author finds cross-category effects, which means that a purchase by a consumer in one category might have a negative influence on the neighbor's purchase probability in a different category. We would expect rational consumers not to be influenced by the purchases of their neighbors at all. Thus, it can be assumed that the participants in this study were acting irrationally, as their purchase probability increased through social effects.

Finally, we discuss another example of social contagion, but this one occurs in a conventional retail context. Argo, Dahl, and Morales (2008) analyze how social influence in the context of touching and contamination of products by attractive consumers can impact other consumers. Physical touch in a retail setting is a paradox. On the one hand, touch helps consumers to inform themselves about the product and to make better purchase decisions. On the other hand, they dislike others touching the products they want to buy, as they feel that this contaminates the products. However, using experiments, this study shows that there are certain conditions under which the touch of others can have positive outcomes, so-called positive consumer contagion. The authors show that consumers prefer products that have been previously touched by highly attractive others. For example, when male consumers believed that a highly attractive female had touched a product (i.e., had tried on a piece of apparel), their product evaluations improved. However, the same was not true for female consumers when other attractive females had touched the product. As the second experiment shows, the effect of attractiveness level on consumer contagion outcomes is moderated by sex. Thus, positive contagion outcomes were only realized when the opposite sex performed the touch. As in the previous example, it can be assumed that consumers act irrationally in this context, as their product evaluations should not be influenced by the previous touch of other individuals. As the products are not diminished in terms of quality or in any other way that would reduce their value, it is not rational to adapt product evaluations simply based on the occurrence of touch by other individuals.

3.4. Promotion

3.4.1. Promotion & Non-Standard Preferences

Consumers often employ self-control to avoid hedonic temptations. However, consumers sometimes force themselves to indulge. Kivetz and Simonson (2002) study self-control in sweepstakes and lotteries – a popular example of "true" nonprice promotions (Gedenk, Neslin, and Ailawadi 2006). Consumers still pay the full price for a good or a service, but they also obtain the opportunity to win something. Kivetz and Simonson (2002) show, in an experiment with a between-subjects design and real choices, that the likelihood of pre-committing to indulgence (i.e., the choice of a hedonic luxury over cash) is enhanced when the consequences of the decision will be realized farther in the future. In particular, female respondents have a higher preference for a hedonic prize with a value of $80 (described as *"a luxurious one-hour facial cosmetic treatment or a one-hour pampering massage"*) over $85 in cash if the lottery drawing takes place in 14 weeks compared to 1 week. Hence, time-preferences are inconsistent and cannot be explained using the standard model because the preference order should not change given different time horizons. In the case of the longer time delay, Kivetz and Simonson (2002) explain this effect with lower concreteness and psychological costs. An additional interesting finding, which is also inconsistent with the standard model, is that some respondents choose the hedonic luxury ($80) over the cash prize with a higher value ($85). A rational decision-maker would always pick the cash prize and then purchase the specific hedonic luxury with a positive residual amount (given that the willingness to pay is high enough).

Regarding reference dependence, Kivetz (2003) relates the utility function of prospect theory to the (risky) choice of rewards in the context of frequency (or loyalty) programs. By manipulating whether effort is required to be eligible for the reward, Kivetz (2003) shows that the presence of effort shifts the reference point such that consumers require some form of definite compensation and prefer a sure-small reward (1,000 miles in a frequent-flyer program) vs. a larger-uncertain (risky) reward (1/50 chance to win 50,000 miles). Additionally, the author shows that intrinsic motivation acts as a moderator in this relationship and attenuates the effect of effort on risk preferences. Kalra and Shi (2010), on the other hand, use cumulative prospect theory, modeling the reference dependence of the value function, loss aversion, and non-linear probability weighting, to find a value-maximizing optimal reward structure for sweepstakes. The reference dependent value function, in particular, allows distinguishing the behavior of different types (high-brand- and low-brand-valuation) of consumers. For the latter, the reference point will be higher, as those consumers require compensation for switching costs. Kalra and Shi (2010) empirically validated their hypotheses that the value-maximizing reward structure of the sweepstake will depend on the type of consumer and their risk-aversion or risk-neutrality in gain domains. In particular, they show that high-brand-valuation risk-neutral consumers have a greater likelihood of choosing "winner-takes-all grand prize only" types of sweepstakes, while riskaverse consumers prefer sweepstakes with more than one prize. In contrast, low-brand-valuation consumers prefer sweepstakes of one grand or multiple larger prizes bundled with many small prizes. Because the utility in the standard model depends on the overall wealth level, the observed shifts in risk preferences in both Kivetz (2003) and Kalra and Shi (2010) cannot be explained by effort and switching costs.

In the case of campaigns for donations, social preferences are important in the context of advertising. Sudhir, Roy, and Cherian (2016) run a large-scale field experiment with approximately 185,000 prospective new donors and investigate how the content and framing of information in mail advertisements affects donation choices and amounts for a specific program in India (*"Support a Gran,"* which supports elderly destitute women). Note that under the standard model, no reaction to the advertisements should be expected. The authors have 12 experimental treatments (plus a control group) with four factors: (1) whether the victim is identified or not, (2) whether the victim belongs to the same religion as the donor (Hindu or Christian), (3) whether the situation of the victim is described as a loss or not, and (4) whether the yearly donation is framed as a daily or monthly amount. Whereas the last factor is a clear framing effect, the first three factors are closely related to nonstandard preferences. Sudhir, Roy, and Cherian (2016) hypothesize that evoking sympathy leads to prosocial behavior and "more giving" because of a reference-dependent sympathy bias. Although the donation rate is quite low in general (approximately 0.2%), the results show that all four factors indeed have positive and significant main effects, leading to a higher probability of donation and (conditional on donation) higher donation amounts. Hence, this empirical evidence is interesting because it shows not only that social preferences exist (i.e., donation rate > 0%) but also that simple communicative elements of an advertisement can moderate the results because of reference dependence and framing. Another study related to social preferences, that of Dubé, Luo, and Fang (2017), investigates prosocial behavior in the context of direct marketing and specifically the interplay of discounts (price-promotions) and donations as nonprice-promotions. In a large-scale field experiment, the authors manipulate the discounts and donation levels of SMS coupons for a movie and send the coupons to the mobile phones of subscribers who live close to a theater. The experiment reveals several interesting effects: (1) When there is no price discount, redemption rates are positive if the amount of the donation is greater than zero, i.e., social preferences exist. (2) If donations are zero, the redemption rates strictly increase in discount depth, which is consistent with standard economic theory. (3) However, if both promotional instruments (discounts and donations) are combined, the results are mixed. High donations do not work well together with deep discounts, implying a negative interaction effect. Dubé, Luo, and Fang (2017) explain these results with a self-signaling effect: consumers update their own beliefs about themselves, and price discounts crowd out the self-inference of altruism (Benabou and Tirole 2006).

Lim and Chen (2014) investigate the role of social preferences in sales force incentives, which subsequently lead to better face-to-face communication with the customer. As rational agents only include their own payoffs in the utility, following the standard model assumptions – i.e., individual incentives for the sales force personnel – should be most efficient. In contrast, Lim and Chen (2014) find that in certain situations, e.g., in the case of strong social ties among the (two) group members, group incentives can be more effective. Notably, this is the case if the payment scheme puts less focus on the contribution of each teammate and if group members cannot accurately observe the amount of effort of other group members. Lim and Chen (2014) further show that a behavioral model with the utility function, including the payoffs of the group members, better predicts the observed dynamics compared with the standard model.

3.4.2. Promotion & Non-standard Beliefs

Concerning non-standard beliefs, optimism biases might lead to higher efficiency of a promotional instrument that has an element of uncertainty, such as sweepstakes or delayed promotion (e.g., mail-in rebates). For example, Goldsmith and Amir (2010) provide experimental and field evidence that sweepstakes, which offer an unknown probability of receiving a more valued or inferior product (with a not-too-large value variance), can have comparable efficiency (in terms of purchase likelihood) to that of sweepstakes with a certain reward of only the valued product and are more efficient than sweepstakes that offer the inferior product as a reward. The authors suggest, and show through an experiment, that this advantage is due to consumers acting as if they expect to receive the best possible outcome, i.e., they are overoptimistic about their chances. Further, overconfidence might come into play in the context of delayed promotions (e.g., mail-in rebates), resulting in redemption “slippage” (failure to redeem). In particular, Soman (1998) finds that, while keeping the face value of the discount of the mail-in rebate constant, the amount of effort does not affect the purchase likelihood when there is a delay between purchase and redemption. At the same time, the purchase likelihood of the promoted brand is higher when there is such a delay. The author suggests that this behavior can be explained by overconfident consumers who underestimate the amount of effort required. Therefore, a mail-in rebate that is potentially unappealing to a rational decision-maker might seem appealing to the (irrational) overconfident consumer. Gourville and Soman (2011) further suggest that the strength of one's intrinsic motivation acts as a moderator of this relationship.

Narayanan and Manchanda (2012) study the casino gambling behavior of individuals using real behavioral data (revealed preferences) from a leading casino company in the US. The authors focus on gambling addictions as well as belief-based biases, such as the gambler's fallacy and the hot hand myth. Such biases can be empirically identified because the data has a panel structure, where each consumer decision (playing and the amount of the bet) is observed multiple times. In addition to demographic variables, the data also include the marketing activities of the casino company that can be related to the customers' gambling behavior. These targeted promotional efforts (so-called "comps") aim at increasing the duration of play and the amount bet once a consumer has begun to play; and they are set based on the past behavior of the player. Narayanan and Manchanda (2012) find a negative (positive) effect of last wins (losses) on current betting behavior, which is consistent with the gambler's fallacy (i.e., based on the standard model, the past results of a random event should not have an effect on current behavior). Furthermore, males and Hispanics display stronger evidence of the gambler's fallacy. The casino's marketing activities have a positive effect on the probability of playing and the amount bet. Comparing the elasticities of effects, it can be shown that the elasticity of last losses is approximately the same as the elasticity of comps, implying that the effect of the gambler's fallacy is equivalent to the effect of targeted marketing in the casino industry. Also note that comps have an intertemporal effect because of the gambler's fallacy.

3.4.3. Promotion & Non-Standard Decision-Making

Keeping the face value of the discount offered by the promotion constant, Cheema and Patrick (2008) provide evidence, from both hypothetical and field experiments, that framing the time window as expansive (anytime) vs. restrictive (only) affects the evaluation of the promotion by consumers and interacts with their mind-set (deliberative vs. implemental). In particular, while the time window is the same in the experimental conditions, the way it is communicated differs: either the redemption is possible any time between 12:00 and 4:00 pm (expansive frame) or only between 12:00 and 4:00 pm (restrictive frame). The results suggest that respondents with an implemental mind-set, who focus on the feasibility of the offer, prefer and have higher redemption rates for the expansively framed promotions, while the opposite is true for respondents with a deliberative mind-set, who evaluate the offer on a more abstract level. Note that under standard rationality assumptions, there should be no difference in the redemption rates because there is no difference in the time frames.

Chakravarti and Xie (2006) also provide evidence of framing effects in the context of advertising by comparing the efficiency of comparative (direct and indirect) and non-comparative advertising in markets with competing technological standards. In such markets, the purchase decision is, in fact, more complex due to the higher uncertainty regarding which standard will prevail and the potential costs related to ending up with the standard that eventually loses. The authors provide empirical evidence that in the case of standard competition, comparative advertising, which communicates relative vs. absolute information, results in a higher choice likelihood of the advertised brand (44-69% choice share) than does non-comparative advertising (19%). At the same time, direct comparative advertising (in which a particular competitor brand is mentioned) proves to be more efficient than indirect (69% vs. 44% choice share), as it provides a specific reference point for consumers. The same attribute information is communicated in all three advertising formats; therefore, based on standard rationality assumptions, there should not be such discrepancy in the choice shares.

Regarding limited attention, Zhang, Wedel, and Pieters (2009) study how the characteristics of feature advertisements (e.g., size, location on the page) affect sales and the mediating role of attention in these relationships. In particular, they match attention (eye-tracking) data (collected in a lab) for feature ads used by top supermarket retailers in the Netherlands with the retracted design characteristics of these feature ads and actual sales data from the GfK panel. Using a Bayesian model, which accounts for the mediating role of attention and the potential endogeneity of the key variables, they find that attention to feature ads, measured by gaze duration, results in higher sales above the effect of the mere presence of the feature ad. Further, they find support for the mediating effect of attention on the effects of feature characteristics on sales. One interesting finding is that a cluttered display page reduces the efficiency of feature advertisements and their ability to generate sales.

Related to persuasion in advertising, Cowley (2006) analyzes how consumers react to wildly exaggerated claims for products or services. In a lab experiment, respondents saw different print advertisements for three different products/services (Harbor Bistro, Alternative Bar, City Cruise line). The ads differ in their levels of exaggeration (fact, low puffery, high puffery). For example, the Harbor Bistro ad claimed that the bistro was “the very best bistro in Sydney” (low puffery), “the ultimate dining experience” (high puffery), or simply made the factual claim of offering “dining with a harbor view.” The results show that although consumers can identify exaggerated claims as less credible than factual claims, their brand evaluations are inflated after exposure to exaggerated claims. Persuasion bias can explain this outcome. In the standard model, on the other hand, consumers should take into account that the information provider has an incentive to “over-sell” their product/service, and thus brand valuation should not vary across experimental conditions. In a similar vein, Cox and Cox (2001) analyze the persuasive effect of advertising for early-detection products (e.g., mammograms). In particular, they examine the effect of alternative approaches to communication (statistical facts vs. anecdotes) and the framing (gain/loss) of the consequences of early-detection behavior. The results of an experiment show that anecdotal messages have an interaction effect with framing: Loss-framed anecdotal advertisements have a higher perceived informational value and lead to a greater perceived likelihood of having a mammogram after seeing the ad. However, this interaction effect is not present for statistical information. Therefore, this study shows that advertising might lead to a persuasion bias, but only if the content is anecdotal and gain/loss-framed.

4. Managerial Implications & Avenues for Future Research

As the previous section shows, there are numerous biases that affect consumer behavior across marketing instruments. Understanding these behavioral effects offers marketing practitioners many opportunities to increase profits by designing their marketing strategies accordingly. Indeed, many companies are already taking advantage of their customers’ predictably irrational behavior. For instance, regarding product, firms are integrating consumers’ social preferences into their product strategy. Fair trade labels (e.g., for coffee) are a case in point; there is ample empirical evidence from surveys that consumers are willing to pay more for socially responsible products. Next, regarding price, firms benefit by framing price information. For example, consumers perceive tensile claims (e.g., savings of __% and more) to offer lower savings than other non-tensile (objective) claims (e.g., savings given as a coupon), as the low end of the price promotion is highlighted in tensile claims. Moreover, regarding place, firms already optimize their store layouts and displays (i.e., a physical form of framing) such that in-store travel distance, and hence unplanned spending, is increased. Finally, regarding promotion, we observe that firms capitalize on consumers’ presumed overconfidence. Many firms are using sweepstakes that have an unknown probability of receiving a more valued or inferior product (with a not-too-large value variance), which have comparable efficiency (in terms of purchase likelihood) because consumers act as if they expect to receive the best possible outcome.

Having presented examples of how firms already make use of their consumers' irrational behavior, the question arises whether companies could benefit even more from focusing on behavioral effects or whether they already sufficiently incorporate such effects into their marketing strategies. A first point to consider is that while firms already exploit several opportunities that follow from non-standard preferences, beliefs, and decision-making in their marketing strategies, such as reference dependence or framing, there might be other biases that are difficult to observe (e.g., overconfidence) that firms might not have fully exploited yet. Thus, additional attention to underrepresented biases would offer marketing managers more opportunities to influence consumer behavior.

In particular, among the three classes of deviations from the standard economic model, we find that much research in marketing addresses consumers' preferences as well as their decision-making, while much less attention has been devoted to studying their beliefs. For example, there is extensive research on reference-dependent preferences (e.g., reference price theory) and framing (especially in promotion research), while the marketing research on the impact of belief-based biases, such as overconfidence or projection bias, is still rather scarce. With respect to the marketing instruments, we observe that numerous studies documenting behavioral biases in marketing address issues mainly related to product, price, and promotion. Studies focusing on place are rather scarce. One explanation for this observation is that issues around place often do not explicitly refer to the established terminology of behavioral economics. However, based on our literature search, it also appears that fewer studies are analyzing place.

In addition to the implications we draw from our review, current and future developments will influence firms' understanding of behavioral biases and the ways in which firms can influence consumer behavior. First, the boundaries between online and offline shopping are increasingly blurring (Brynjolfsson, Hu, and Rahman 2013). The ability to track (potential) buyers across channels allows sellers to draw a much more holistic picture of their customers. As a consequence, firms can develop much more sophisticated and targeted methods that account for behavioral biases and use these to influence consumer behavior. For example, firms could target consumers at times where they are most resource-depleted or when they are in close proximity to stores to increase unplanned buying. In terms of product offerings, the study of the endowment effect for different touch interfaces showed how important it is that firms create their websites in a mobile-friendly way so that consumers are affected by the endowment effect via the combination of touch and product visualizations, in almost the same way as they are affected in physical stores. Relatedly, online channels enable firms to exploit context and framing effects with less effort because websites can be easily adapted and changed for each customer, and native advertising in mobile search can lead to persuasion. Context effects are of particular interest for new online services, such as music and movie streaming services or offline/online channels for publishing journals. Firms need to understand how behavioral biases work given that many new products and services, which are sold on- and offline, are increasingly complex and difficult for consumers to evaluate.

Second, the emergence and increasing interaction of consumers with new technologies have the potential to moderate behavioral biases. Marketing managers need to react to these developments but can also actively employ these technologies to track and influence consumer behavior. While some digital offers are already likely to affect the way behavioral biases are playing out today, other technologies are still in an early stage of development but are likely to affect behavior in the near future. For instance, with the help of technologies such as RFID or Bluetooth Beacons, consumer behavior can be tracked and immediate action can be taken to influence the in-store behavior of consumers. Using these technologies, retailers can offer mobile coupons based on the in-store location of their customers or current products in the customer's shopping basket, both of which can increase the path traveled in-store to expose consumers to more in-store stimuli that may lead to more unplanned buying. In addition, video screens with real-time messages and electronic shelves can be used to interact with customers and potentially influence their behavior (Dukes and Liu 2010).

Amazon's delivery service "Prime Now" is another example. "Prime Now" offers delivery within the next (couple of) hour(s). Thus, consumers are not restricted to shopping hours and do not have to wait for deliveries for (at best) one day; instead, they can immediately satisfy their needs, which is very likely to induce consumers to engage in more impulse buying.

Yet another example is augmented reality – a technology that already exists but is not yet used to its fullest potential. Using augmented reality in online shopping can help consumers imagine items such as furniture in their actual apartments, which could influence behavior via biases such as the endowment effect. Finally, in the foreseeable future, additional distribution channels will develop, for which consumers' behavior needs to be assessed. For example, cars may potentially develop into a new channel, as autonomous driving will allow new activities to be performed inside the car while traveling.

Third, the increasing share of digitally mediated sales enables sellers to collect massive amounts of high-quality data (i.e., disaggregated across individuals and time) about their customers' behavior and to track direct responses to their marketing measures. These data enable firms to better understand their customers, to detect their behavioral biases and to eventually capitalize on them. Digital markets may also give rise to new behavioral biases because most of the "classical" biases were first discovered and studied long before the age of the Internet. For example, research suggests that consumers are developing lower rates of information recall because Google offers an external memory (Sparrow, Liu, and Wegner 2011).

The interplay of online-offline convergence, new technologies, and data allows marketing managers to individualize the targeting of (potential) customers. Marketing managers are able to offer personalized products, to engage in personalized pricing (e.g., dynamic pricing), to customize digital interfaces (e.g., adaptive websites) and to individually communicate promotions to their customers. As a result, firms can learn about the heterogeneity of behavioral biases in their customer bases and can adapt their marketing mix on the customer's level accordingly.

However, as much as firms may benefit from exploiting behavioral biases, such a strategy may also backfire. First, consumers may become aware of firms' practices and turn away from a brand if they feel outsmarted. In addition, regulators and consumer protection agencies are likely to interfere if firms are unwilling to commit to staying within reasonable boundaries. Therefore, to prevent being externally regulated, marketers should consider setting internal boundaries within which they want to conduct business.

Avenues for future research can be divided into methodological issues and research questions. First, in terms of methodology, the increased use of online and mobile channels offers researchers the possibility to more easily obtain detailed field data and to conduct field experiments, particularly in marketing (Lambrecht and Tucker 2015). Researchers should use these methods to replicate and to extend behavioral effects in the marketing literature. Regarding field experiments, it would be interesting to study behavioral biases with real consumers instead of convenience samples, such as student samples. Furthermore, field experiments across multiple countries, industries, and domains are of particular interest to enhance the generalizability of such studies because specific behavioral biases are most likely heterogeneous along these dimensions. Also related to methodological aspects are structural models and advances in experimental designs that explicitly allow for behavioral biases (see e.g., Dubé, Hitsch, and Jindal 2014). Such efforts would also be highly valuable for future research.

Second, with regard to unexplored research questions, our review of papers dealing with non-standard preferences, beliefs, and decision-making in the marketing literature indicates that some biases are not as thoroughly addressed as others. Specifically, belief-based biases such as overconfidence are not addressed as often as other biases. Yet, this class of deviations from the standard economic model has been shown to be important in other business disciplines such as finance (e.g., Glaser, Nöth, and Weber 2004). Therefore, belief-based biases merit future research in the marketing domain. Likewise, looking at the elements of the marketing mix, existing research focuses more on product, price, and promotion than on place. In the face of the developments and technological advancements discussed above, the convergence of the online and offline channels, as well as behavioral biases related to place, appear to be particularly promising areas for future research. Emerging technologies such as augmented reality are likely to have an effect on existing behavioral biases, and in addition, might cause new forms of irrational behavior. More generally, the existence and persistence of biases across all elements of the marketing mix need to be re-evaluated in light of new technologies.

Additionally, questions concerning the existence of biases in competitive environments are currently neglected. Neoclassical economists often claim that behavioral biases must be irrelevant because they cannot survive in competitive markets. However, behavioral economists argue that some biases may not only survive competition but may even be reinforced by it. And because most markets are competitive, we believe that the behavioral biases discussed in the marketing literature also persist. Nevertheless, we do not yet know much about the actual consequences of non-standard behavioral patterns in the context of competitive environments.

5. Conclusion

In this paper, we aimed to bring together research from behavioral economics and marketing. We reviewed previous marketing research documenting behavior that deviates from neoclassical predictions and mapped the findings onto a structure that involves elements from both economics and marketing. In this way, we provide examples of each group of biases (i.e., non-standard preferences, non-standard beliefs, and non-standard decision-making) from empirical marketing research, from both the field and the lab. From these examples, we derive implications for marketing research and practice.

This paper caters to marketing researchers and behavioral economists alike. We contribute to the respective research domains by introducing marketing researchers to the terminology employed in the field of behavioral economics and thereby help them to better navigate the extensive list of documented biases in this field. As for the field of behavioral economics, we provide scholars with easy access to the rich marketing literature containing applied empirical research. More generally, researchers may benefit from this review by pursuing the proposed avenues for future research. Likewise, marketers and practitioners can benefit from the derived implications.

The combination of economics and psychology is not only what is known as behavioral economics, economics and psychology are also the two most influential disciplines underlying marketing (Ho, Lim, and Camerer 2006). Therefore, many studies from marketing research explicitly draw on theories and models of behavioral economics or are concerned with research questions that could be analyzed through the lens of behavioral economics, although this is not always particularly apparent. We illustrate this by mapping and discussing papers from marketing research that study behavioral biases onto a combined structure from behavioral economics (i.e., DellaVigna 2009) and marketing (the four marketing instruments). We find that for product, price, and promotion, the connection to behavioral economics is often very explicit, while the commonalities regarding place are much less salient. As for the three classes of deviations from the standard economic model (i.e., non-standard preferences, beliefs, and decision-making), we find that much research in marketing addresses consumers' preferences as well as their decision-making, while much less attention has been devoted to studying their beliefs.

Regarding managerial implications, we observe several similarities across all marketing instruments. First, it can be established that many firms are aware and already take advantage of many of the behavioral biases discussed in this paper. However, current and future developments will influence the firms' understanding of behavioral biases and the way in which firms can influence consumer behavior. The boundaries between online and offline shopping are increasingly blurring, enabling firms to track their (potential) buyers across channels and thus to draw a much more holistic picture of their behavior. Consequently, firms seeking to influence consumer behavior can develop much more sophisticated and targeted methods that account for behavioral biases.

Moreover, digital technologies are driving new developments that affect consumer behavior. Firms will need to assess how behavioral biases change in the face of these new developments and how the marketing mix needs to be adapted accordingly. We find examples across all marketing instruments: from new products and services emerging through digital technologies, to increasingly prevalent forms of pricing such as dynamic pricing, to changes in distribution due to the increased use of online channels and non-stationary devices such as mobile phones, to a shift in communication from traditional marketing channels such as TV to digital channels. An advantage of the increasing share of digitally mediated sales is that it enables sellers to collect massive amounts of high-quality data about their customers' behavior, which lets them track direct response to their marketing measures.

Taken together, the interplay of online-offline convergence, new technologies, and data allows marketing managers to individualize the targeting of (potential) customers. Consequently, firms can learn about the heterogeneity of behavioral biases in their customer base and can adapt their marketing mix to the customer's level accordingly.

Avenues for future research can be found both for methodological issues and research questions. In terms of methodology, the increased use of online and mobile channels offers researchers the opportunity to obtain detailed field data more easily and to conduct field experiments. With regard to unexplored research questions, belief-based biases such as overconfidence are not addressed as often as other biases and thereby merit future research. Likewise, looking at the instruments of the marketing mix, place is relatively unexplored. In the face of the developments and technological advancements discussed above, particularly the convergence of the online and offline channels, behavioral biases related to place appear to be a promising area for future research. Furthermore, emerging technologies such as augmented reality are likely to have an effect on existing behavioral biases and, in addition, might cause new forms of irrational behavior. Additionally, questions concerning the existence of biases in competitive environments are currently neglected, leaving room for studying behavioral biases in the context of competitive environments.

We must also acknowledge some limitations. Because we focus on prime examples of the different "bias – marketing instrument" combinations, this review does not present a complete overview of the behavioral biases studied in marketing. Consequently, we cannot quantitatively determine the relative importance of the different biases for the four marketing instruments but can only provide a qualitative assessment of this relationship. Nevertheless, we believe that this review offers a valid picture of the behavioral biases discussed in the marketing literature.

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Appendix

Marketing Instrument	Group of Biases	Bias	Marketing Keyword	References
Product	Non-standard preferences	Time-inconsistent preferences	• Utilitarian vs. hedonic product choice	• Milkman, Rogers, and Bazerman (2009, 2010)
			• Durable product adoption	• Dubé, Hitsch, and Jindal (2014)
		Reference dependence	• Extended warranties • Product insurance	• Jindal (2015)
			• Endowment effect • Return policy	• Wood (2001) • Wang (2009)
		Social preferences	• Fair trade labeling	• Hainmueller, Hiscox, and Sequeira (2015)
	Non-standard beliefs	Overconfidence	• New product adoption	• Guo (2006) • Meyer, Thao, and Han (2008)
		Projection Bias	• Remote purchases	• Conlin, O'Donoghue, and Vogelsang (2007)
			• Durable goods purchases	• Busse et al. (2012, 2015)
		Law of small numbers	• Investment decisions	• Johnson, Tellis, and MacInnis (2005)
	Non-standard decision making	Choice architecture/Framing	• Package labeling	• Levin and Gaeth (1998)
			• Delivery option	• Loewenstein (1998) • Malkoc and Zauberman (2006)
			• Local choice context • Preference for "all average" • Product line design	• Dhar, Nowlis, and Sherman (2000) • Dhar and Simonson (2003) • Simonson (1989) • Kivetz, Netzer, and Srinivasan (2004) • Rooderkerk, van Heerde, and Bijmolt (2011) • Tversky and Simonson (1993)
		Limited attention	• Information overload	• Malhotra (1982) • Payne et al. (1992)
			• Consideration/choice set construction	• Bronnenberg and Vanhonacker (1996)
			• Inattention to attributes	• Gilbride, Allenby, and Brazell (2006) • Swait, Popa, and Wang (2016)
			• Left-digit bias	• Lacetera, Pope, and Sydnor (2012)
		Persuasion and social pressure	• Peer effects	• Narayan, Rao, and Saunders (2011)
		Emotions	• Branding	• Romani, Grappi, and Dalli (2012)

Price	Non-standard preferences	Time-inconsistent preferences	• Quantity discounts • Consumption impulses	• Wertenbroch (1998)
		Reference dependence	• Reference prices • Price sensitivity	• Kalyanaram and Winer (1995) • Mazumdar, Raj, and Sinha (2005) • Novemsky and Kahneman (2005) • Bell and Lattin (2000)
			• Price-quality heuristic	• Gneezy, Gneezy, and Lauga (2014)
		Social preferences	• Pay What You Want	• Spann et al. (2017) • Krämer et al. (2017) • Schmidt, Spann, and Zeithammer (2014)
			• Charitable giving	• Jung et al. (2017)
			• Price fairness	• Campbell (1999)
	Non-standard beliefs	Overconfidence	• Tariff choice	• Lambrecht and Skiera (2006) • DellaVigna and Malmendier (2006) • Grubb (2012)
		Projection Bias	• Usage prediction • Habit formation	• Acland and Levy (2015)
		Law of small numbers	• Store image	• Cox and Cox (1990)
	Non-standard decision making	Choice architecture/Framing	• Price presentation • Price promotion	• Krishna et al. (2002)
			• Partitioned prices	• Morwitz, Greenleaf, and Johnson (1998)
		Limited attention	• Price knowledge	• Dickson and Sawyer (1990)
		Persuasion and social pressure	-	
		Emotions	• Bidding behavior	• Ding et al. (2005)
Place	Non-standard preferences	Time-inconsistent preferences	• Impulse buying	• Stern (1962) • Vohs and Faber (2007)
		Reference dependence	• Endowment effect • Need for touch	• Brasel and Gips (2014)
		Social preferences	-	
	Non-standard beliefs	Overconfidence	• Online search	• Brynjolfsson and Smith (2000) • Johnson et al. (2004) • Clemons, Hann, and Hitt (2002)
		Projection Bias	-	
		Law of small numbers	-	
	Non-standard decision making	Choice architecture/Framing	• In-store marketing • Store layout	• Hui et al. (2013)
			• Recommendations • Search cost • Ranking effects	• Diehl (2005) • Alba et al. (1997) • Dellaert and Häubl (2012)
			• Channel effects	• Ghose, Goldfarb, and Han (2013)

		Limited attention	-	
		Persuasion and social pressure	• Social influence	• Gardete (2015) • Argo, Dahl, and Morales (2008)
		Emotions	-	
Promotion	Non-standard preferences	Time-inconsistent preferences	• Sweepstakes and lotteries • Hedonic consumption	• Kivetz and Simonson (2002)
		Reference dependence	• Probabilistic rewards • Frequency (loyalty) programs	• Kivetz (2003)
			• Reward structure of sweepstakes	• Kalra and Shi (2010)
		Social preferences	• Charitable giving • Direct marketing	• Sudhir, Roy, and Cherian (2016) • Dubé, Luo, and Fang (2017)
			• Sales force incentives	• Lim and Chen (2014)
	Non-standard beliefs	Overconfidence	• Probabilistic promotion	• Goldsmith and Amir (2010)
			• Delayed promotion • Redemption slippage	• Soman (1998) • Gourville and Soman (2011)
		Projection Bias	-	
		Law of small numbers	• Casino gambling	• Narayanan and Manchanda (2012)
	Non-standard decision making	Choice architecture/Framing	• Redemption rates	• Cheema and Patrick (2008)
			• Comparative advertising	• Chakravarti and Xie (2006)
		Limited attention	• Feature advertisement	• Zhang, Wedel, and Pieters (2009)
		Persuasion and social pressure	• Exaggerated claims	• Cowley (2006)
			• Anecdotal claims	• Cox and Cox (2001)
		Emotions	-	

Table A: Overview of Behavioral Biases and Marketing Keywords with References