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The Sales Velocity Effect on Retailing

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Abstract

In an increasingly crowded marketplace, retailers need innovative ways of promoting products to their consumers. E-commerce retailers have utilized to great effect lists of top ranked products to promote product sales; the higher the sales rank, the more likely consumers buy that product. This influence to buy, based on observing what others bought is known as observational learning (OL). Prior OL research assumed that OL arises from observing a static outcome, such as the current sales rank of a product. However, prior research on intertemporal choice showed that people prefer outcomes with increasing trends over stable or decreasing trends. This suggests that observing an increasing sales rank, denoted as sales velocity, would have a positive effect on purchase likelihood. We conducted three studies to test the sales velocity effect. Results show that sales velocity has a significant effect on likelihood of purchases, reversing even participant preferences for a product with a higher sales rank. This effect is consistent across four broad products tested. For researchers, by joining the two previously disparate branches of research in OL and intertemporal choice, we addressed a gap in OL research which previously ignored the velocity dimension of OL. For retailers, the study demonstrated the impact of the sales velocity metric on making choices, and thus they could use sales velocity data as a cost-effective marketing tool for specific products.

Keywords: Observational learning; Consumer choice; Online experiment; Internet marketing; Social influences; Social learning

Introduction

Consumers are often influenced by the purchase choices of others when they make their own purchase choices (Chen, Wang, and Xie 2011; Hanson and Putler 1996). Furthermore, 80% of sales are influenced by online information.[1] Recognizing this, retailers have leveraged e-commerce portals to facilitate popularity-based marketing tools such as a top ten sorted list of sold products. The underlying mechanism is denoted as observational learning (OL) and describes the observation of others' actions without considering the underlying rationale (Bikhchandani, Hirshleifer, and Welch 1998). The consumer subsequently infers some state of reality from the actions of others and takes the same action.

This OL effect is widely deployed as a marketing tool and is an effective form of online social influence (Chen, Wang, and Xie 2011; Duan, Gu, and Whinston 2009; Tucker and Zhang 2011); OL is often implemented as a list of best selling products sorted by sales rank. It has been already shown that the higher the sales rank, the more likely consumers buy that product (Cai, Chen, and Fang 2009).

Prior research (Chen, Wang, and Xie 2011; Duan, Gu, and Whinston 2009; Tucker and Zhang 2011), however, implemented OL as a metric static in time, namely as the current sales rank of a product; however, psychology literature on intertemporal choice showed that the satisfaction with an outcome (ex. a person's current salary) is positively related not only to the "position" of an outcome (ex. the current salary) but also the rate at which this outcome changes over time (the "velocity" — ex. how much the current salary changed from the previous level) (Hsee and Abelson 1991; Hsee, Abelson, and Salovey 1991). Following this logic, the current implementation of OL — sales rank — also has a previously unconsidered velocity counterpart,

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[1] Sources: Hoar et al., 2013.

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which we dub "sales velocity". Implemented as the change of sales rank with respect to time, sales velocity should also positively influence the likelihood of a product purchase. However, it is still open whether the presence of sales velocity metrics would actually influence consumers' likelihood of purchase.

From a practical viewpoint, if sales velocity is shown to have an effect on consumer choices, it may also provide a cost-effective promotional vessel for addressing the problem of non-promoted products in inventory. Today, recommendation systems in e-commerce which display top-selling products decrease overall sales diversity (Fleder and Hosanagar 2009); consumers are congregated to the most popular products and ignore the rest of the retailer's assortment. Since a retailer can have over 100,000 products, this results in the majority of inventory never seen or made salient to consumers, incurring a cost for keeping the product in stock and additional cost to promote them. If a retailer wants to selectively promote these lesser known products, today there is little recourse other than a series of increasing discounts — a form of negative dynamic pricing that cuts into retailer's margins (Chinthalapati 2006; Elmaghraby and Keskinocak 2003; Gallego and Van Ryzin 1994). Since a product with high sales velocity might not necessarily be the one that has a high sales rank, we examine whether sales velocity might provide an alternative and cost-effective promotional vessel that exposes lesser known and lesser sold products. To our knowledge, there is no research which examined which of the retailers' products exhibit high sales velocity, and therefore could be promoted with this feature, nor research on sales velocity's influence on a consumer's likelihood of purchase. The contribution of this paper is therefore to conceptualize and empirically study sales velocity, which describes the popularity rise of a product over a pre-defined period of time. The contribution to research is that these results extend OL research into a hitherto unexplored dimension, namely its change with respect to time by combining OL research with the research stream on intertemporal choice. For practitioners, the results of this work show how to leverage the sales velocity effect as a cost-effective and easy to operationalize tool for promoting selected products in online retailing as well as in traditional in-store retailing via smartphones.

The remainder of the paper is structured as follows. We review related literature and develop the hypotheses. Then, we present and discuss three studies that explore the effect of sales velocity on consumers' likelihood of purchase and the boundaries of this effect. In a general discussion, we outline limitations of this research and provide practical implications. Finally, we conclude the paper and identify opportunities for future research.

Related Literature

Observational Learning

Observational learning ("OL") is a social learning phenomenon. The effectiveness of social learning for influencing consumer behavior has been studied early in marketing research (Herr, Kardes, and Kim 1991; Richins 1983). Social learning is defined in various ways: In the psychology perspective (Cialdini and Goldstein 2004; Deutsch and Gerard 1955), social learning can be either persuasive by suggesting to the customer what actions are socially acceptable by others (normative social influence), or by suggesting that information from others is evidence of some state of reality (informational social influence). In the economics perspective, Libai et al. (2010) and Chen, Wang, and Xie (2011) describe social learning as customer-to-customer (C2C) interactions, distinguishing between the depth of information available. They distinguish between merely observing on the surface what others have done, broadly categorized as OL (Bikhchandani, Hirshleifer, and Welch 1998) and interacting with others/seeking their opinion, where the predecessors' reason or motivation for the choice is clearly indicated, known as word of mouth (WOM) (Chen, Liu, and Zhang 2011; Chevalier and Mayzlin 2003). The psychology and economics perspectives are not mutually exclusive and can overlap; OL and informational social influence are analogous to each other. As such, the research gap which we will address in this paper is important to both perspectives of social learning and is relevant to both the psychology and economics community.

There are several aspects that render OL attractive not only on the level of research, but also from a practitioner's view. On a practitioner level, OL is less complex to employ than WOM, since all that is needed is a popularity metric (such as the volume of sales of a product), which is typically already gathered by the retailers' Point of Sales (PoS) systems. Furthermore, effective implementations of OL came with recent advances in information systems technology, particularly in the area of online shopping. Online shopping platforms such as Amazon.com or eBay.com enable consumers to view information on product popularity in the form of number of sales and product reviews. WOM however, requires active user generated content (for example, written product reviews). Since retailers already have PoS data, the deployment of an OL system faces less "cold-start" problems compared to WOM. Additionally, WOM has already been fairly well studied both online (Chen, Liu, and Zhang 2011; Chevalier and Mayzlin 2003) and offline (Bowman and Narayandas 2001; Herr, Kardes, and Kim 1991). In contrast, OL has only recently been employed for exploratory research in persuasive systems, mostly in e-commerce portals (Chen, Wang, and Xie 2011; Duan, Gu, and Whinston 2009; Tucker and Zhang 2011), while research gaps remain in investigating alternative OL metrics and dimensions. Accordingly, within the bigger picture of social learning, we focus on OL social persuasion rather than WOM.

The Sales Velocity Research Gap

Observational learning was defined as the "inference resulting from rational processing of information gained by observing others" (Bikhchandani, Hirshleifer, and Welch 1998, p 153); although this definition is broad enough to encompass both learning from observing the actions of others, as well as observing

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the rate at which the actions occur (this rate change of the actions can be thought of as the "velocity"), the OL literature subsequent to Bikhchandani, Hirshleifer, and Welch (1998) dealt primarily in the context of the former. These include studies of OL in e-commerce portals which implemented OL as a static sales rank (Chen, Wang, and Xie 2011), website clicks in a wedding product portal (Tucker and Zhang 2011), or even in the area of organ donation waiting lists (Zhang 2009). In all these cases, the velocity dimension is not considered.

However, research beyond OL suggests that observing the velocity component of others' actions could have an effect on purchase decisions. Research on intertemporal choice, for example, has shown that consumers have a preference for a sequence of improving outcomes (Loewenstein and Prelec 1993); that is they prefer things that get better and better, and that this effect gets stronger with the speed with which the improvement occurs over time (Hsee and Abelson 1991; Hsee, Abelson, and Salovey 1991; Hsee, Salovey, and Abelson 1994). Extending this into the area of retailing, an example would be a product's sales velocity — that is, how much a product has improved in sales or sales rank over a period of time.

But up until now, it has not been shown that the concept of improving outcomes could be leveraged as a marketing tool, or that there is a link between the sequence of improving outcomes and the velocity component of OL. To confirm this, we therefore did a forward and backward search for papers which cited either core OL papers (Bikhchandani, Hirshleifer, and Welch 1998), the aforementioned studies (Hsee and Abelson 1991) or models of social learning reviewed by Chamley (2004). We further searched for "rate change", "sales velocity", "velocity outcomes" and "velocity performance". We applied our search to the databases ABI/INFORM, Business Source Complete (EBSCO), the Web of Science and Google Scholar, as well as the top ten marketing journals defined in analysis by Hult et al. (1997) and Steward and Lewis (2009). We considered articles from 1991 to February 2014.

The articles found do not leverage velocity effects as a marketing tool: Improving outcomes was used as a diagnostic metric within firms and in the supply chain (Bronnenberg and Sismeiro 2002; Groves et al. 2011; Sandoh and Larke 2002), studied for its effect on goal striving (Chang, Johnson, and Lord 2009; Elicker et al. 2009) and evaluated for its effect on a firm's satisfaction with logistics service providers (Briggs, Landry, and Daugherty 2010). Although parallels to the retail domain exist (e.g. in the study by Briggs, Landry, and Daugherty 2010, the logistics provider can be seen as the product which the firms — the customer — have to choose between), we see that there is a research gap in evaluating this phenomenon in the retail domain. This motivates an extension of these results in the context of e-commerce portals, where it can be leveraged to actuate behavior change of consumers; and furthermore, with a controlled experiment, so that one can gain deeper insight on the effect.

In a retailing context, we might therefore expect that revealing velocity information of product sales would positively influence the likelihood of purchase. From an OL point of view, this would be akin to observing not only the actions that others have taken but also the rate at which they are taken. A product's sales velocity might also embody the idea of a product being discovered and being better received, leading to a positive product evaluation for the deciding consumer.[2] Additionally, as we might expect from the accessibility–diagnosticity model of information (Feldman and Lynch 1988), if a piece of information is accessible and useful for a choice at hand, it would be accepted. Accordingly, depending on the context of the product or situation, the change in a product's popularity could give a variety of informative signals to the consumer, and therefore influence their purchasing choices. For example, for fast moving goods and routine purchases such as groceries, it is known that consumers occasionally seek variety in their purchases (Van Trijp, Hoyer, and Inman 1996), sometimes even eschewing their known, pleasurable favorites for the sake of variety (Ratner, Kahn, and Kahneman 1999). It therefore follows that in this situation, rather than the most popular product, which a consumer is likely to have tried already, the consumer might rather choose a less popular product — provided that they get some positive signal. The alternative product's rising popularity might provide this signal.

Development of Hypotheses

The Sales Velocity Effect

The research gap as discussed above suggests that sales velocity might be able to influence a consumer's decision-making, since it represents an improving outcome. We thus propose that the higher the sales velocity of a product, the more likely a consumer will choose it, all else being equal. However, in any choice set, realistically it is unlikely that the choices are equal in rank. Therefore, any study of the sales velocity would have to account for differences in the current rank between choices. Thus we formulate our main hypothesis as:

H1. Given a choice of similar product alternatives, when the sales velocity is high (low), the likelihood of purchase of that product is higher (lower).

While the first hypothesis is aimed at establishing the effect, we further explore some boundary conditions that might boost or reduce the effect of sales velocity on likelihood of purchases.

The Role of Numeric Framing

The sales velocity cue can play a major role in influencing consumer choice. It can be presented in many different ways including as different units (ex. as percentage or in raw numbers), icons (ex. an up arrow), colors (ex. a green number for the velocity), and a combination thereof. In this paper, we focus on the widely established area in research and practice of unit framing, which has been used in the past for optimizing the

[2] We acknowledge that a product can decrease in sales rank. In our main study, we focus on establishing the sales velocity effect in the positive direction — similar to a best sellers list, which lists only positive observational learning information. We examine the effect of negative sales velocity in separate study.

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effect of price discounts; thus we expect a similar result on the framing of sales velocity information. The idea of how choice problems are framed can affect our cognitive judgment and preferences dates back to the work by Kahneman and Tversky (1984), which presented an example on how the way a number is represented influences perception of the underlying quantity. In the marketing literature, much focus has been on price discount framing (DelVecchio, Lakshmanan, and Krishnan 2009; Krishna et al. 2002; Chen, Monroe, and Lou 1998). In the study by Chen, Monroe, and Lou (1998) for example, they found that consumers perceived a price reduction in absolute dollar terms to be larger than the same price reduction framed in percentage terms when the number displayed for the price reduction was larger than the number displayed of the percentage reduction. In other words, the unit and framing had a significant influence on people's perceptions of the quantity, and taking this logic into the area of rank change, we would expect the same to be true. Namely, if we have a sales velocity metric, then we would expect the representation that leads to the largest number to have the strongest effect. The phenomenon exhibited in Chen, Monroe, and Lou (1998) can be described by the numerosity effect (Bagchi and Li 2011; Chen and Rao 2007; Kruger and Vargas 2008; Monga and Bagchi 2012; Pandelaere, Briers, and Lembregts 2011; Zhang and Schwarz 2012); namely, when something is expressed in alternative units, the perception of magnitude increases if the unit is on a finer grained scale. In Pandelaere, Briers, and Lembregts (2011), it was shown that consumers see a bigger difference between two products when the warranty information was represented in months than years. The effect is attributed to people focusing on the numbers rather than the units. This effect has been largely ignored in e-commerce and since sales velocity can be represented in different forms as well, we expect that the effect of sales velocity as hypothesized in H1 to be higher when the sales velocity is expressed in a unit that leads to larger numerical values. Therefore, we develop the following hypotheses:

H2a. Consumers perceive an objective rank change of a product to be higher when it is expressed in a unit that leads to larger numeric values (and vice versa).

H2b. A product evaluated to have a high (low) rank change has a stronger (lower) sales velocity effect on the likelihood of purchase.

The Negative Sales Velocity Effect

Up until now we were primarily concerned with boosting sales due to positive sales velocity in OL. Given a period of time, a product can increase in sales rank (positive sales velocity) but also decrease in sales rank (negative sales velocity). This provides an important boundary of the sales velocity effect since sales velocity is not yet widely implemented, retailers should know the effects of negative sales velocity before making a decision to implement sales velocity in general. The literature on loss aversion suggests that losses are perceived to be stronger than gains of equivalent size and that the perception of the loss is relative to the position from where the loss occurred (Hardie, Johnson, and Fader 1993; Kahneman and Tversky 1984; Tversky and Kahneman 1991). Accordingly, one would expect a negative sales velocity to have a larger negative impact on the likelihood of purchase, than the reverse case with positive sales velocity. Accordingly, we formulate our hypothesis as follows:

H3a. Given a choice of similar product alternatives, a product with a decreasing (increasing) sales velocity has a lower (higher) likelihood of purchase.

H3b. Given a choice of similar product alternatives and the same relative sales velocity, the effect of the decreasing sales velocity on the likelihood of purchase is stronger than the effect of increasing sales velocity.

Overview of Studies

We conducted three studies to test our hypotheses. Study 1 consists of two parts. In Study 1, we first test the basic sales velocity effect; we test whether consumers have a higher likelihood in purchasing a product when the sales velocity is high (H1). Second, we test for the numerosity effect to see whether the framing of the sales velocity information can lead to changes in the perception of the sales velocity (H2a) and subsequently to changes in the likelihood of purchasing a product (H2b). In Study 2, we explore the generalizability of the sales velocity effect in the case of different focal products. In Study 3, we finally explore the effect of negative sales velocity on the likelihood of purchases (H3a/H3b).

Study 1: Establishing the Sales Velocity Effect

To investigate H1 and H2a/H2b, we conducted an online consumer choice experiment as follows.

Task

Consumers often have well-established preferences for products (Hoyer 1984) making it difficult in a consumer choice experiment to select a "preference neutral" stimulus with minimal confounds.

Although in a real-world scenario, such preferences would inevitably be present, in a first experiment it is desirable to control against them. For this reason, our consumer choice experiment was based on the agent/principal task common in the marketing literature (for examples, please see Ariely 2000; Diehl and Poynor 2010; West 1996), where the participant (the agent) has to make the best choice on the behalf of another person (the principal) based on the principal's preferences which are transparently given to the participant. In this manner, we aim to neutralize the effect of individual attitudes or individual involvement to a particular product or product domain.

Accordingly, participants read a scenario that asked them to imagine that they wanted to treat a good friend who likes chocolate. They were told that this friend has tried out a wide variety of chocolate before, including the most popular ones, so therefore the friend wants to try something new and refreshing. The scenario then told the participants to imagine that they subsequently checked an online e-commerce store serving their market, scrolled through the options, and now have to consider two offerings.

Subsequently, participants were given a tutorial where they were taught and tested on how to interpret the rank information on the e-commerce store. We note that most e-commerce sites do not force onto or give users a detailed explanation of their popularity metrics and how they are computed; however for internal validity and to ensure the users would understand the information in the task, we provided this tutorial. After the tutorial, participants were presented with the stimuli.

Stimuli Development

Selecting the Focal Product

The domain of retail, online and offline, covers a wide variety of domains and products, ranging from clothes to electronics to food. Without loss of generality, since we are implementing a principal–agent task where personal preferences are taken out of the equation, for the purpose of this experiment, we chose chocolate as a focal product. Because chocolate is sold at both online and offline physical retailers (ex. Walmart sells chocolate both in their online store and also in their bricks and mortar chains), the results of this study can be relevant to both channels. Furthermore, chocolate is also an example of a repeatedly-bought and hedonic good (Voss, Spangenberg, and Grohmann 2003), which facilitate variety seeking behavior (Van Trijp, Hoyer, and Inman 1996); as discussed in the hypothesis formation, popularity change might aid choices in a variety seeking situation.

Since our stimuli will consist of sales rank data, we analyzed a year of receipt data from our European physical grocery retailer partner in order to have a basis for realistic sales rank numbers and to validate how realistic it is to use sales velocity to promote products like chocolate, given its actual sales behavior, and also what would be the potential impact of such a promotion. The receipt data comes from a single store, and consists of over 150,000 unique receipts covering a total of two million transactions, which map to 19,374 unique products sold that year. We first looked at how often these products were sold, since the stimuli deals with sales rank data. These 19,374 products sold followed an extreme long-tail distribution in terms of aggregate sales; that is, only a few products have a large frequency of sales (the "hits"), while the majority sell infrequently (the "niches") (Anderson 2006). The distribution of the first 500 products are depicted Fig. 1. In Fig. 1, the circles depict a product's average sales per week and the associated sales rank. For that same product at the given sales rank, the triangles then indicates the average rank change of the product. What becomes immediately apparent from this distribution is that the high ranking products exhibit a very low rank change — i.e. they sell well each week and tend to stay that way throughout the year.

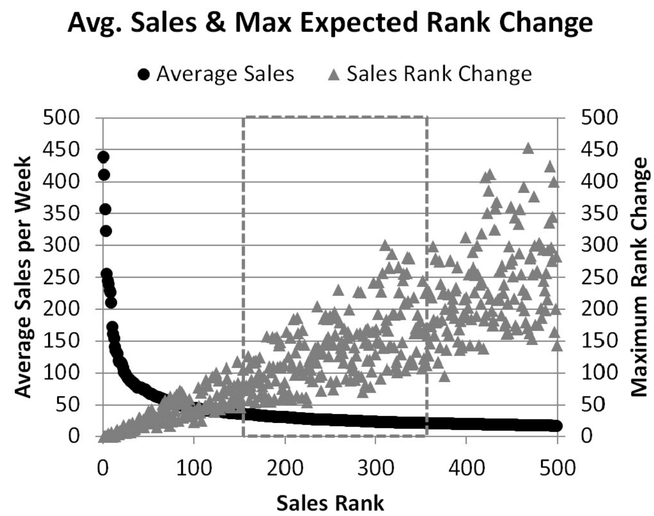

Fig. 1. A product's average sales per week and the associated sales rank. For that same product at the given sales rank, the triangles then indicates the average rank change of the product, and the dashed box the mid tail.

We note that Fig. 1 contains the retailer's products, irrespective of which product category the product belonged to; to check the generalizability of the sales rank and sales rank change distributions, we have also looked at the sales distributions within each of the retailer's 900 product categories and verified that the average sales and sales rank change trend also holds true at the category level. Namely, that the average sales follow a long tail distribution and the maximum sales rank change grows the further from the head of the distribution. An excerpt is shown in Fig. 2.

Since there are no universally accepted cut-off points between the niches and the hits for the sections a long-tail distribution,[3] for the purpose of further discussion and analysis, we use the following definitions: a product is a "hit" if it is in the top 1% in terms of total number of products sold in a year, in the long tail if it is in the bottom 90% of products, and those in between we call the mid tail. Some characteristics from the retailer partner are shown in Table 1.

As Table 1 shows, the long-tail products make up a large segment of the retailer's revenue and have a large sales velocity — accordingly they could be well promoted with sales velocity, but promoting a long-tail product is not helpful to the physical retailer, who has limited inventory. Therefore, a long-tail product would be inappropriate as a focal product in our experiment. Similarly, the hits in the distribution are also inappropriate as a focal product. Although the hits in the long-tail head sell well (over 30 units per week), they exhibit low sales velocity, form only 19% of the sales revenue, and furthermore are often items which consumers already buy regularly — for the data of our retailer partner, 75% of our receipts contain an item from the top selling 1% of all products. This is not a problem in the e-commerce context for products which consumers infrequently buy (ex. cameras), since consumers are unlikely to have bought the recommended popular product. However, for the grocery retail domain at least, a top

[3] For differing models, please see Brynjolfsson, Hu, and Simester (2011) and Elberse (2008).

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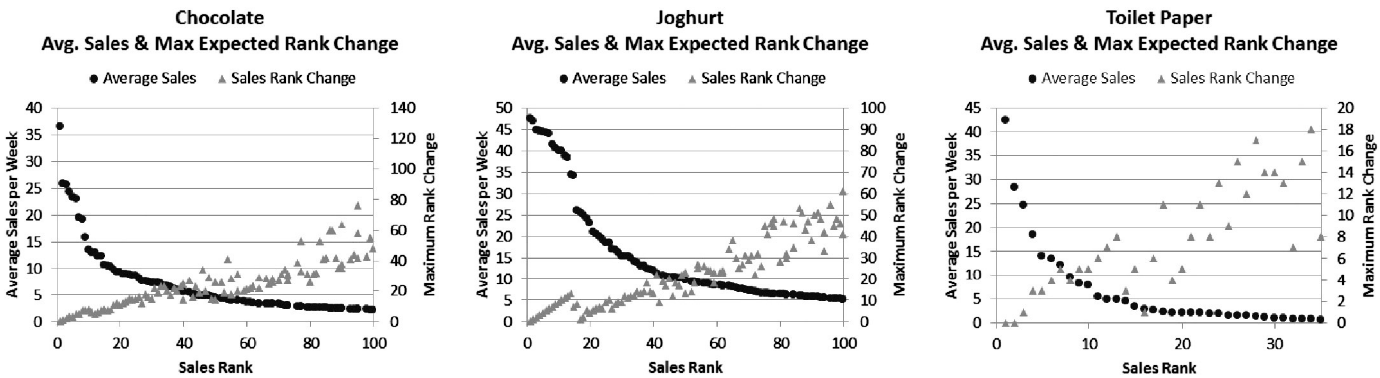

Fig. 2. Average sales and maximum rank change distributions for select product categories.

seller list could suffer from irrelevancy since — as noted in our data — most of the top selling products are already bought by the majority of consumers, so from the consumer point of view, there is nothing new. For the retailer, this leads to no additional new purchases. Furthermore, the insights from the field of recommendation systems (Adomavicius and Tuzhilin 2005; Zhou et al. 2010) caution against continuously recommending products that are too close to what a user already buys, as it reduces the relevancy of the recommendation. Thus, a classical OL metric which would expose hit products is neither appropriate for physical grocery retailers or their customers and thus a hit product should not be used as a focal product in our experiment either.

In contrast, mid-tail products exhibit high sales velocity and additionally make up a large segment of the retailer's revenue. The differing sales velocity and revenue characteristics between hits and mid-tail products suggests that sales velocity can be an effective form of marketing persuasion in promoting specific mid-tail products, thereby increasing revenue. Sales velocity avoids the aforementioned problem of promoting the most popular products which consumers already buy — a problem that did not exist for infrequently bought e-commerce goods, where OL has historically been deployed. In this data set, we found that chocolate is in the mid-tail, exhibiting high sales velocity. Taken together, these results suggest that using a mid-tail product (like chocolate) in the experiment that has revenue potential for retailers, is valid with respect to actual sales data, and therefore an appropriate choice.

Development of the Choice Profiles

Each chocolate offering was presented as a profile consisting of the product, the price, the product description, the product rank and — depending on the experimental group — a different representation of the product sales rank change. The rank change information varied depending on which of the experimental groups the participant was in. Participants were randomized into either the control group (shown product rank only), the rank change group (product rank + rank change), or the numerosity group (product rank + rank change in percentage). The profile pairs within each experimental condition were designed to be as similar as possible except for their rank change metric and its representation. This would allow us to study the effect of rank change and its framing: comparing the rank change group with the control group addresses H1, and comparing the rank change group with the numerosity group addresses H2a/H2b. A decomposition of the product profiles and experimental groups is depicted in Fig. 3.

The product profile components, listed below, were designed and pre-tested (n = 184) for similarity:

- *Choice set size*: Here the choice set size refers to the size of the market for that category when browsing an e-commerce site. For sites such as Amazon.com, for categories like cameras, there are thousands of cameras on offer, while for memory cards there are only hundreds. We assume that the current rank and the past rank (see below) are only meaningful relative to the choice set size (i.e. a product with a sales rank of 9 in a market where there are 10 products is probably perceived worse than when the market has 1000 products). Our pre-test found that having a larger choice set size minimized the perceived difference between consecutively ranked products, but beyond 100 products the perceived difference did not change. Therefore, we chose a choice set size of 100.
- *Current rank*: The two products in each comparison received a rank of 50 and 51 respectively; the pre-test showed that participants (correctly) identified 50 as the better ranked product and perceived the difference between 50 and 51 to be small. We will confirm this in the main study with a manipulation check.

Table 1
Product characteristics for "hit", "mid-tail" and "long-tail" products for a physical retailer.

	Average week-to-week rank change	# of products in this category	Average units sold per week	Combined revenue
"Hit"	171.5	192	>30.3	19%
"Mid-tail"	726.4	1742	30.3 ≥ units sold ≥ 5.61	41%
"Long-tail"	844.7	17,440	<5.61	40%

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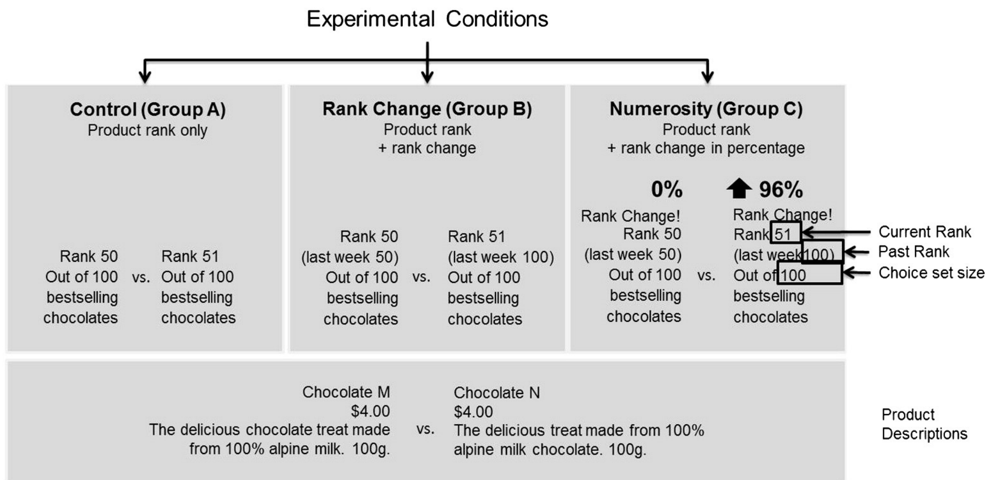

Fig. 3. Components in a product description; the descriptions were made as similar as possible, and parameters such as the current rank, past rank and choice set size were controlled for in a pre-test.

- *Product descriptions*: To minimize differences between the profiles except for the ranking information, the product names were generically chosen as Chocolate M or N, their respective prices were set equal to each other, and the product descriptions were written with only subtle variations between them. The pre-test confirmed that the product description text was indeed perceived as similar.

Finally, for the manipulation itself, within each product pair we aimed to polarize rank change between the offerings. For the rank change component, we examined the year of purchasing data from our grocery retailer and found that chocolate in the mid-tail could fluctuate up to 100% in rank change, while more popular chocolate does not change in rank at all week to week. Accordingly, one product received a rank change of 0% while another received a rank change of 96%. The % rank change was calculated as (Past_Rank − Current_Rank) / Current_Rank × 100. To cue the consumer that the rank change was positive, we placed an up arrow next to the change for rank change. (Since most popular e-commerce websites use arrows, we used this de-facto standard which consumers already know.) We also note that other definitions of calculating this % rank change could exist; however since this study examines numerosity from the point of view of designing a proper stimuli, only the end numerical magnitude of the rank change measure is sufficient. To create a conservative experimental design, we then assigned the less popular product the higher rank change and the more popular product zero rank change. Therefore, if people choose the product with the higher rank change, it would be in spite of it being the less popular product.

Participants

We recruited 120 participants from an online panel (Amazon Mechanical Turk, https://www.mturk.com) (μ_{age} = 32, σ_{age} = 11, 45% female) for the study.

The participants were paid a token amount for the study and were mostly from the United States (95% from USA; the rest from the United Kingdom, Ireland and Canada). In line with Mason and Suri (2012), we excluded responses from 6 participants, whose responses did not pass attention-check questions in the survey, resulting in 114 samples (a 95% pass rate). The reliability of participants and the demographics are in-line with past studies conducted on the Mechanical Turk (Downs et al. 2010; Goodman, Cryder, and Cheema 2012; Mason and Suri 2012) which showed that Mechanical Turk participants were as reliable as a "traditional" panel and could replicate classical behavioral experiments. There were no significant differences in results between genders.

Measures

After being presented with the stimuli, the participants then had to first indicate which of the two products they were more likely to buy, i.e. they were asked to indicate the likelihood of purchase. In line with the study by Kruger and Vargas (2008), this was measured on an unnumbered seven point scale, anchored by product M on one end and product N on the other end of the scale.

Subsequently, on another screen participants had to compare the two profiles in terms of sales rank change; they had to indicate which product they thought had the higher sales rank change. This was measured in the same manner as the likelihood of purchase. This measure served to determine whether the numerosity effect changed the perception of the sales rank change.

Attention and Confounding Checks

On the same screen as the sales rank change comparison, participants had to compare the two profiles in terms of price and sales rank; for each profile pair, they had to indicate which product they thought had the higher price and higher sales rank. These too were measured on the same scale and anchors as the main measures. Price served as an attention-check question, since the two offers were equal in price in all groups; therefore the correct answer would be a “4”. Those who failed this question were not considered for analysis in the study. Sales rank was a confound check; since the sales rank information remained the same across all groups, there should be no difference between them. The wording of the questions is given in Appendix A. The presented order of the profiles was counterbalanced between participants; the product with the higher rank was randomly assigned to product M or N. In the analysis, the product with the higher rank was labeled “M” (represented by a score of “1” on the seven-point Likert scale) and the score was reverse coded when the higher ranking product was assigned to “N”.

As another check, we also asked them questions concerning their involvement when it comes to chocolate purchases for themselves and also for others; the intention was to check whether the scenario selected had an involving product (chocolate) and situation (purchases for another). The scales are from Chandrashekaran 2004. Finally, we also asked participants how large they thought the differences were between the product profiles on a seven-point Likert-scale ranging from very small (1) to very large (7). Since group B and group C share the same content as A, with only the addition of the rank change information, in order to isolate the effect of this manipulation, it would be desirable for the perceived difference in group A to be significantly small.

Results

Prior to the main analysis, several checks were conducted. First, since most of our items were measured with the same method (a seven point Likert scale), we tested for the common method bias using Harman’s one factor test (Podsakoff and Organ 1986; Podsakoff et al. 2003). We conducted a principal component analysis for these variables in the study and found multiple factors with eigenvalues greater than one; accordingly, no single factor explained the majority of variance and the common method bias was not significant.

Second, prior to the main analysis, we tested for homogeneity of variances and normality for responses to the main measure “likelihood of purchase”, and also for the checks for sales rank change and sales rank. The Levene statistic for testing homogeneity of variances was significant ($p < 0.05$) so therefore, the variances between groups differ significantly. Additionally, the Shapiro−Wilk test was significant ($p < 0.05$) so the data is not normally distributed. Accordingly, the assumptions of ANOVA and the t-test are violated and thus we conducted the non-parametric Kruskal−Wallis and Mann–Whitney U tests on the likelihood of purchase measure and for the sales rank change and sales rank checks when looking for significant differences between groups.

Attention and Confounding Checks

For the price attention checking question, a sample of $n = 114$ (95% of participants) passed and were considered for further analysis.

For the sales rank, since the current rank was the same across all groups, there should be no differences across experimental groups. The Kruskal−Wallis test confirmed this and did not show a significant effect of the experimental group on the reported sales rank ($H(2) = 3.326$, $p = 0.190$). Pairwise Mann–Whitney U also did not show any significant effect either ($p > 0.017$[4] for all pairwise comparisons between groups). Therefore, the sales rank was perceived (correctly) to have no significant differences across experimental groups.

For the involvement check in chocolate purchases, involvement in purchases for one self was high ($\mu = 5.12$, $\sigma = 1.65$) as well as that for others ($\mu = 4.92$, $\sigma = 1.48$), suggesting that the scenario depicted, as intended, an involving product (chocolate) and situation (purchases for another). Finally, for the last check, we had asked participants how large they thought the differences were between the product profiles on a seven-point Likert scale from very small (1) to very large (7). For group A, which formed the basis profile pairs for all other groups ($\mu = 1.81$, $\sigma = 1.25$), a one-sample t-test showed that the perceived difference lies significantly below the neutral scale value of four, $t(41) = -11.32$, $p < 0.001$*. This assured us that the base profile pairs we generated were, as intended, very similar, allowing us to infer that the differences in the other experimental groups came entirely from the manipulation.

The Sales Velocity Effect

In order to test H1, we first conducted a Kruskal–Wallis test between groups for the likelihood of purchase. There was a significant effect of the experimental group on the reported sales rank ($H(2) = 20.22$, $p < 0.001$*). We then conducted two Mann–Whitney U tests to compare the control group A with the two groups where sales velocity was present (groups B and C) to find where this effect was.

A summary of the descriptive statistics and Mann–Whitney U tests for the main dependent measure is in Table 2. A total of 114 subjects participated after filtering from the attention check questions. For interpreting the descriptive statistics, recall that all outcomes were measured on an unnumbered seven point scale, anchored by “Definitely product M” on one end and “Definitely product N” on the other end of the scale, with “No Difference” in the middle. “Definitely product M” was coded as a “1” and “Definitely product N” was coded as a “7”.

Referring to Table 2, the paired Mann–Whitney U tests also show a significant difference between the control group A and the numerosity group C, and between control group A and the rank change group B. In other words, both groups where the rank change manipulation was present (groups B and C) were significantly different than group A. Descriptive statistics (see Table 2) for the three groups show that in group A, people prefer the higher ranked product, are less sure in group B, and show a preference for the lower ranked product under a numerosity framing in group C.

[4] A Bonferroni correction of $1/n_{comparisons}$ was applied to control for the Type 1 error that arises from multiple comparisons; with three comparisons, all Mann–Whitney U effects were thus reported at a 0.0167 level of significance to obtain an even more strict requirement for significance.

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Table 2
Summary of paired Mann–Whitney U statistics (given by U) for the likelihood of purchase. The * indicates significant p-values after a Bonferroni correction was applied.

Likelihood of purchase	Groups involved	Result	Conclusion
Descriptives μ (σ)	Group A (n = 42)	2.64 (1.27)	Sales velocity groups B and C have higher likelihood of purchase than the control.
	Group B (n = 32)	3.69 (1.99)	Furthermore, p < 0.0167* for both "A vs. B" and "A vs. C", so, H1 is supported.
	Group C (n = 40)	4.53 (1.88)	Effect size in "A vs. C" > "A vs. B" so H2b is supported.
Mann–Whitney U tests U, effect size r, p	A vs. B	U = 467, r = 0.26 p < 0.0167*	
	A vs. C	U = 357, r = 0.50 p < 0.001*	
	B vs. C	U = 487, r = 0.21 p = 0.0395	

From the empirical data, H1 is therefore supported; rank change has a significant effect on the likelihood of purchases and that it weakened the likelihood of choosing the higher ranked product.

The Numerosity Effect

In order to test the second hypothesis, a Kruskal–Wallis test showed that there were overall differences between the three groups for the perceived rank change ($H(2) = 66.680$, $p < 0.001$*). Pair-wise Mann–Whitney U tests were conducted to see where the differences lie. The results are given in Table 3.

In Table 3, descriptive statistics show that in group A, when no rank change information was presented, participants simply chose the higher ranked product ($\mu = 3.31$, $\sigma = 0.52$), but correctly identified the higher rank change product in groups B ($\mu = 5.72$, $\sigma = 1.55$) and C ($\mu = 6.50$, $\sigma = 1.28$). Notably, there was a significant difference between groups B and C, which showed that the numerosity effect was present in C and did lead to a difference in perceived rank change.

These results provide evidence that our manipulation of the rank change was successful — and also that the numerosity effect significantly changed the perception of the rank change. Thus, H2a is supported: the numeric framing influences perception of sales velocity too.

To address H2b — i.e. whether this change in perception of sales velocity leads to a stronger sales velocity effect on the likelihood of purchase — we first conducted a Mann–Whitney U test between the control group and the numerosity group ($U = 83.5$, $r = 0.82$, $p < 0.001$); the test showed that the numerosity group C is significantly different from the control group in the likelihood to purchase, indicating that with numerosity present, the sales velocity effect is still significant. Furthermore, as per Borenstein et al. (2009) we computed the effect sizes for our two treatment groups. We find that the effect size (0.50) is also larger than the case without the numerosity framing (0.26). Thus, H2b is supported. Mean values of the likelihood of purchase for group C ($\mu = 4.53$, $\sigma = 1.88$) is also larger than for group B ($\mu = 3.69$, $\sigma = 1.99$). These results are summarized in Table 2.

Discussion

For the first hypothesis, the sales velocity, operationalized by the rank change, had a positive effect on the likelihood of purchase, as evident by the significant differences of the two rank change groups (group B and group C) with respect to the control — this confirms our main hypothesis (H1). This result bolsters the results in intertemporal choice that, indeed, the velocity of an improving outcome positively influences consumer evaluation of choices, and that this outcome can be operationalized in the rank change metric.

The result also reveals and addresses a large gap in OL research, which previously only considered current outcomes arising from others' choices, without factoring in the velocity dimension of these outcomes. Counterintuitively, the positive signaling from an improving product was even able to reverse the preference for a higher ranked one. In the control group, nobody chose to buy the worse ranked product, but a significant number of those in the rank change groups did. This preference reversal occurred even though the sales rank heuristic is much more commonplace in practice, and therefore

Table 3
Summary of Paired Mann–Whitney U statistics (given by U) for the sales rank change. The * indicates significant p-values after a Bonferroni correction was applied.

Sales rank change	Groups involved	Result	Conclusion
Descriptives μ (σ)	Group A (n = 42)	3.31 (0.52)	The perceived rank change for numerosity group C is larger than B.
	Group B (n = 32)	5.72 (1.55)	Furthermore, p < 0.0167* for "B vs. C" so, H2a is supported.
	Group C (n = 40)	6.50 (1.28)	
Mann–Whitney U tests U, effect size r, p	A vs. B	U = 145, r = 0.71 p < 0.001*	
	A vs. C	U = 83.5, r = 0.82 p < 0.001*	
	B vs. C	U = 457, r = 0.30 p < .0167*	

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more familiar to consumers. The implication is that this metric can be leveraged by retailers to promote mid-tail products, which are not necessarily the most popular, but typically exhibit good gains in sales rank. Our results also extend the findings of Briggs, Landry, and Daugherty (2010) who showed that velocity metrics of performance is positively correlated with a firms' perception of the providers; in particular, we showed with a controlled experiment that there is also an influence on choices, in a context where retailers can use the result for their marketing initiatives. Our results also suggest that the general findings of studies in velocity outcomes from Hsee, Abelson, and Salovey (1991) also hold true in the context of marketing.

For the second hypothesis H2a, there was a significant difference in the perceived sales rank change between the rank change group B and the numerosity group C, which showed that the numerosity effect was present and did lead to a significant difference in perceived rank change H2a is thus supported. Also, group C's higher effect size and a greater likelihood of purchase, as evident by the increased mean, supports H2b.

Study 2: The Sales Velocity Effect with Different Products

Study 1 showed that effect of sales velocity is quite strong for a particular type of product — in this case it was the highly hedonic and relatively fast moving class of chocolate. However, the effect of sales velocity might be less or more pronounced depending on the characteristics of the product marketed.

We note that from an economic perspective of observational learning, the role of the product characteristics should play no role in the observation and interpretation of other shopper's actions. The positive signal that is inferred from observing others' choices should only be a function of how many others have chosen that same product (e.g. Chen, Liu, and Zhang 2011; Chen, Wang, and Xie 2011; Duan, Gu, and Whinston 2009), and as per Study 1, the velocity at which was chosen. However, since each of these economic studies had focused on a single product category (cameras and software respectively), they might have ignored the differential effects of observational learning that may exist across product categories. There is a research gap in systematically controlling for different product characteristics in doing a comparative study of the effect of observational learning.

Study 2 aims to address this. Since there are an infinite number of products available, it is therefore useful to apply a product classification for the purpose of studying the boundaries of the sales velocity effect. In this study we extend the results of Study 1 to include four additional products sampled from two common product classification paradigms: the hedonic paradigm and the non-durable goods paradigm.[5] In the hedonic paradigm, a hedonic good is one that "relates to the multisensory, fantasy and emotive aspects of product usage experience" (Hirschman and Holbrook 1982; Holbrook and Hirschman 1982) — that is, there is an affective component from consuming the product. Examples of such products in the area of grocery retail for example are chocolate, mixed nuts and bubble bath (Chandon, Wansink, and Laurent 2000). It has been shown in the benefit–congruency framework by Chandon, Wansink, and Laurent (2000) that the extent of hedonism in the product affects how consumers respond to the type of sales promotions (which they classified as utilitarian — ex. price cuts — or hedonistic like free gifts); the promotion is most effective when the promotion and product type are matched in hedonism. For a product that is highly hedonic, such as chocolate for example, a promotion is more effective and satisfying when they provide intrinsic stimulation, fun and self-esteem, such as giving a free sample of the product, which encourages discovering and exploring a previously untried product. On the other hand, price cuts are seen to have low hedonic benefit and therefore are not as effective for these hedonic products. Therefore, a product's extent of hedonism influences the type of promotion that is most effective for it. Accordingly, we investigate whether the sales velocity effect still holds across products of differing degrees of hedonism.

The second paradigm which we investigate is the paradigm of the durable good vs. the non-durable good, and concerns the frequency of which the associated product category is purchased. From a consumer's point of view, a durable good is defined as one that lasts multiple time periods; a consumer who buys a product can continue to use it over time, hence a purchase in the present serves as a substitute for a purchase in the future (Mantena, Tilson, and Zheng 2012; Waldman 2003). As such, durable goods are often not purchased as frequently as non-durable goods and they tend to be more expensive. A non-durable good is the opposite and is one that is purchased frequently and consumed almost immediately upon purchase, and therefore tends to be non-durable. Often cited examples of durable goods include computers and cars, while in contrast, food items are often cited as non-durable goods. It had been found that whether a product is a non-durable or a durable good influenced consumer perceptions of various relevant marketing heuristics. Völckner and Hofmann (2007) found that for durable product, compared to a non-durable good, consumers had a weaker association of a high price being linked to high quality, but this difference decreased with product familiarity; this is in line with the finding that suggested that consumers resort to heuristics often for non-durable goods (Bearden 1982; Burke et al. 1992; Hoyer 1984). Estelami and De Maeyer (2004) found that consumers had a much lower knowledge of price of goods for durables than non-durable goods. Derbaix (1983) found that consumers' perception of risk and uncertainty for purchases differed depending on whether it was a durable or non-durable good. As such, we see that the innate frequency of purchases of a product category matter and influence consumer interaction with these products. Thus we also examine whether the sales velocity effect holds across products of differing purchase frequency.

[5] Due to the many similarities between Studies 1 and 2, for parsimony we note where the procedure and manipulations of Study 2 are the same in Study 1, and refer to the pertinent sections of Study 1.

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Task

The task was exactly the same as that in Study 1, except that the product which the participant was shopping for was randomly drawn from a list of four products. In other words, participants were assigned randomly to one of eight groups. For each of the four products compared, there was a control group where only rank information was given and a sales velocity treatment group where additionally rank change information was given. As per Study 1, the participant proceeded with an agent/principal task and read that they were buying a particular product on behalf of a relative on an e-commerce site. They were then taken to a page that presented two offers of the product in question and subsequently asked to indicate which offer they would buy. After indicating which product they would buy and answering subsequent questions, the task was over.

Stimuli Development

We developed four product profiles, whose selection and design are explained as follows.

Development of the Choice Profiles

As per Study 1, each product offering was presented as a profile consisting of the product, the price, the product description and in the control groups, the product rank. For the treatment groups, we additionally showed the sales velocity information of the product.

The profile pairs within each experimental condition were designed to be as similar as possible, except for the rank change metric and its representation. Unlike Study 1, we only used one representation of the sales velocity across all groups. We used the numerosity representation (group C in Study 1), since in Study 1 we found this manipulation to have the strongest effect on the likelihood of purchase, and as such, this would be the recommended representation in a practical setting. The presented order of the profiles was counterbalanced between participants.

Selecting the Focal Product

We select our four product categories which represent the extreme points of the hedonic and durable axes as follows. For our non-durable, fast moving goods, consistent with Laurent and Kapferer (1985), we chose two products from the hedonic scale: chocolate (high degree of hedonism) and laundry detergent (low degree of hedonism). Both of these product categories are considered to be non-durable goods in past studies that have employed a durable/non-durable goods paradigm (Derbaix 1983; Harlam et al. 1995; Holbrook and Hirschman 1982; Yeo and Park 2006). For our durable goods, consistent with Grewal, Mehta, and Kardes (2004), we selected a vacuum cleaner as our non-hedonic product (Laurent and Kapferer 1985) and we selected televisions as our hedonic product (Voss, Spangenberg, and Grohmann 2003; Zheng and Kivetz 2009) which, as per Laurent and Kapferer (1985), scored similarly in hedonism to chocolate.

Participants

We recruited 366 American participants from an online panel (Amazon Mechanical Turk, https://www.mturk.com) (μ_{age} = 31 years, σ_{age} = 10, 40% female) for the study. The groups and number of participants in each are as follows (Table 4).

Measures

We measured the likelihood of purchase as a main measure; after being presented with the stimuli, the participants then had to first indicate which of the two products they were more likely to buy. The scales were as per Study 1.

Manipulation, Attention and Confounding Checks

Participants also had to compare the two profiles in terms of price, sales rank change and sales rank. Price served as an attention-check question and sales rank and sales rank change were included as a manipulation check. We also asked participants how large they thought the differences were between the product profiles Q and R as a further manipulation check.

In addition to the measures of Study 1, we also measured user perceptions of the product categories' extent of enjoyability and purchase frequency, both on a semantic differential scale, to verify that we indeed selected products that were distinctly hedonic/non-hedonic and durable/non-durable.

Results

Manipulation, Attention and Confounding Checks

For the price attention checking question, a sample of 353 passed (96%) and was considered for further analysis. As per Study 1, Sales Rank Change, Sales Rank and Intention to Buy were not normally distributed as per the Shapiro–Wilk test ($p < 0.05$), so all comparisons for these measures between the control and treatment groups for each of the products were thus conducted with the Mann–Whitney U test instead of the t-test. The perceived differences between product profiles were compared in a one-sample t-test against the neutral value of "4".

A summary of these checks are given in Table 5; all manipulation checks were successful.

Hypothesis Testing: The Sales Velocity Effect

For each of the four products, we applied the Mann–Whitney U test between the control and treatment groups for the Likelihood of Purchase measure. The results are given in Table 6.

Table 4
Groups and number of participants in Study 2.

	Products			
	Vacuum cleaner	Detergent	TVs	Chocolate
Control group	41	41	47	45
Sales velocity group	45	46	46	39

Table 5
Summary of manipulation checks; the * indicates significant p-values ($p < 0.05$) for the corresponding test.

Outcome variable	Test of manipulation	Results for …				Conclusion
		Vacuum cleaners	Detergent	TVs	Chocolate	
Sales rank change	Mann–Whitney U test applied to control vs. treatment group	U = 85 r = 0.83 p < 0.001*	U = 164 r = 0.74 p < 0.001*	U = 110 r = 0.81 p < 0.001*	U = 170 r = 0.74 p < 0.001*	p < 0.05 in all cases; rank change correctly perceived as significantly different from control for all products
Sales rank		U = 897 r = 0.10 p = 0.328	U = 905 r = 0.04 p = 0.681	U = 893 r = 0.21 p = 0.044	U = 731.5 r = 0.18 p = 0.100	p > 0.05 except for TVs; sales rank correctly perceived to be the same across most product profile pairs
Perceived differences in product profiles	One-sample t-test between μ in the control groups vs. "4"	μ = 1.52 σ = 1.05 t(43) = −15.72 p < 0.001* $n_{control}$ = 44	μ = 1.80 σ = 1.17 t(40) = −12.05 p < 0.001* $n_{control}$ = 41	μ = 1.55 σ = 0.97 t(46) = −17.23 p < 0.001* $n_{control}$ = 47	μ = 1.51 σ = 1.06 t(44) = −15.78 p < 0.001* $n_{control}$ = 45	p < 0.05 in all cases and μ < 2 in all cases; thus perceived differences between product profiles were small, across all products
Perceived enjoyment	2-Way ANOVA with whether the product was hedonic or not as one factor, and whether its durable as another factor	μ = 3.45 σ = 1.47	μ = 3.76 σ = 1.28	μ = 6.06 σ = 1.21	μ = 6.20 σ = 1.33	A product being hedonic significantly influenced perceived enjoyability, F(1, 349) = 322.002, p < 0.001*.
Frequency of purchase		μ = 2.74 σ = 1.78	μ = 4.92 σ = 1.53	μ = 3.61 σ = 2.10	μ = 4.93 σ = 1.90	A product being durable significantly influenced purchase frequency F(1, 349) = 79.19, p < 0.001*.

The Mann–Whitney U tests between the control and the treatment groups were significant for all product groups; thus H1 is further supported and is robust in spite of the differing properties of the products. Furthermore, the means of the treatment groups indicate that the presence of sales velocity leads to a higher likelihood of purchase for the frequently purchased products ($\mu_{detergents} = 4.13$, $\mu_{chocolate} = 4.51$) compared to the less frequently bought products ($\mu_{vacuum\ cleaners} = 3.93$, $\mu_{TV} = 3.98$). Likewise, sales velocity seems to exert a higher influence on hedonic products ($\mu_{TV} = 3.98$, $\mu_{chocolate} = 4.51$) as compared to the less frequently bought products ($\mu_{vacuum\ cleaners} = 3.93$, $\mu_{detergents} = 4.13$).

Discussion

Study 2 reaffirmed H1 and added generality to the results: the sales velocity is influential even for products that differ in their characteristics. The descriptive statistics suggest that additionally, the effect is stronger for hedonic and frequently purchased goods — indeed, we see that the effect on the likelihood of purchases is strongest for our originally chosen product in Study 1, chocolate ($\mu = 4.51$), and weakest for its diametric opposite (the non-hedonic, infrequently purchased vacuum cleaner, $\mu = 3.93$).

Study 3: The Negative Sales Velocity Effect

Studies 1 and 2 showed that the effect of sales velocity holds even for a variety of products. However, both studies focused on the effect of positive sales velocity on influencing likelihood of purchases. Study 3 extends these results by examining negative sales velocity. The task was exactly the same as that in Study 2, with the same scenario text, sequence of steps and measures.

Stimuli Development

The profiles followed the same format as that in Study 1 and Study 2; the control and sales velocity group were as per Study 2. Compared to Study 2, we additionally added a third group, the negative sales velocity group (group C). Group C was manipulated to have the same magnitude in % sales velocity

Table 6
Results for the Mann–Whitney U tests and descriptive statistics for the likelihood of purchase. The * indicates significant p-values of the Mann–Whitney U test.

	Likelihood of purchase		
	Mann–Whitney U test U, effect size r, p	Descriptives μ (σ), n	
	Control group vs. treatment group	Control group	Treatment group
Vacuum cleaners	U = 495.5, r = −0.44, p < 0.001*	2.41 (1.207) n = 44	3.93 (1.75) n = 45
Detergent	U = 506.5, r = −0.40, p < 0.001*	2.71 (1.553) n = 41	4.13 (1.721) n = 46
TVs	U = 609.0, r = −0.38, p < 0.001*	2.60 (1.378) n = 47	3.98 (1.880) n = 46
Chocolate	U = 379.5, r = −0.49, p < 0.001*	2.67 (1.297) n = 45	4.51 (1.805) n = 39

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decrease as the increase in group B. Since we know from Study 1 and Study 2 that in the absence of sales velocity (i.e. the control group A), participants are more likely to choose the higher ranked product, to create a conservative design, the decrease in sales velocity was given to the higher ranked product. Thus, if negative velocity would have an effect in influencing sales towards the other (lower) ranked product, it would be in spite of participant preference for the better ranked one. A representation of the product profile as shown to participants is depicted in Fig. 4.

The presented order of the profiles was counterbalanced between participants. We sampled two focal products from Study 2: the vacuum cleaner (low hedonic, high durability) and chocolate (high hedonic, low durability). These were found in Study 2 to respectively have the least and strongest effect from sales velocity in likelihood of purchases. The product descriptions remained the same as that in Study 2.

Participants

We recruited 271 American participants from an online panel (Amazon Mechanical Turk, https://www.mturk.com) (μ_{age} = 31 years, σ_{age} = 10, 39% female) for the study.

Measures

The main measure, likelihood of purchase, and the manipulation and attention checks were identical as per Study 1 and Study 2.

Results

Manipulation, Attention and Confounding Checks

For the price attention checking question, a sample of 257 passed (95%) and was considered for further analysis. As per Study 1, sales rank change, sales rank and likelihood of purchase were not normally distributed as per the Shapiro–Wilk test ($p < 0.05$). Consistent with Studies 1 and 2, we used Kruskal–Wallis and Mann–Whitney U tests with Bonferonni corrections.

For the sales rank manipulation check and for both products, the Kruskal–Wallis test was not significant (for vacuum cleaners, $H(2) = 1.102$, $p > 0.05$, and for chocolate, $H(2) = 5.9$, $p > 0.05$), and all three pairwise Mann–Whitney U tests were not significant ($p > 0.0167$ with the Bonferroni correction). The sales rank was perceived (correctly) to have no significant differences across experimental groups.

For the sales rank change manipulation check, there was a significant effect between groups on perceived rank change (vacuum cleaners, $H(2) = 65.789$, $p < 0.001$* and chocolate $H(2) = 60.192$, $p < 0.001$*). Pairwise Mann–Whitney U tests for the sales velocity groups B and C compared to the control were significant (for both products and both comparisons, $p < 0.001$*), thus as intended, our sales velocity groups were perceived different from the control. Furthermore, the difference between groups B and C were not significant (for both products and comparisons, $p > 0.0167$), as intended. Thus the sales rank change manipulation was successful. Note that in order to compare the perceived rank change between the positive and negative velocity groups (where the rank change was applied given to opposite products), we reverse coded the negative velocity results.

As per Study 2, for both products, the perceived differences between product profiles was significantly different from the neutral value of “4” (for the vacuum cleaner, $\mu = 1.52$, $\sigma = 1.05$, $t(43) = -15.72$, $p < 0.001$*, and for the chocolate $\mu = 1.51$, $\sigma = 1.06$, $t(44) = -15.78$, $p < 0.001$*). Both means are also low (both nearly 1.5). Thus, as intended, the profiles were perceived similar other than their rank change information.

The Negative Sales Velocity Effect

Kruskal–Wallis tests showed there was a significant effect of the sales velocity information on likelihood of purchase (vacuum cleaners $H(2) = 29.643$, $p < 0.001$* and chocolate $H(2) = 36.52$, $p < 0.001$*). We applied pairwise Mann–Whitney U tests to determine between which groups the differences were. The results are given in Table 7.

Referring to Table 7, the paired Mann–Whitney U tests show that the likelihood of purchase is increased towards the lower ranking product when it has positive sales velocity (the group A

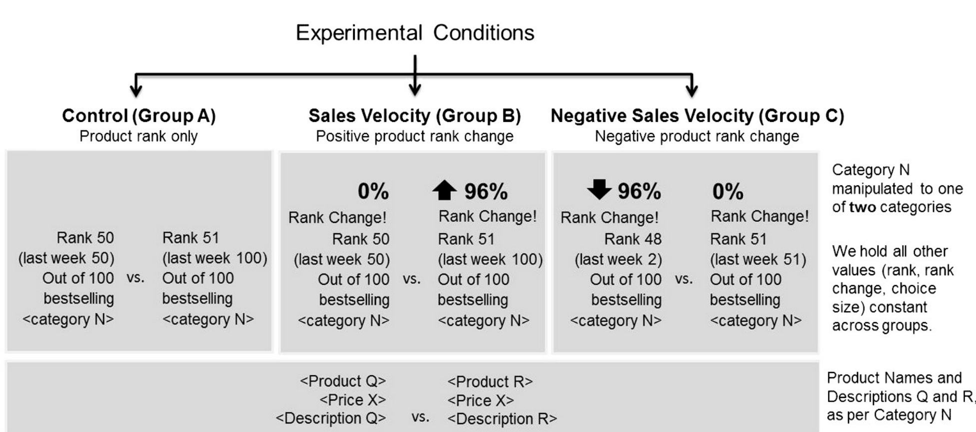

Fig. 4. Components in a product description; two generic profiles Q and R are presented.

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Table 7
Summary of paired Mann–Whitney U statistics for the likelihood of purchase. The * indicates significant p-values of the Mann–Whitney U test.

Likelihood of purchase	Groups involved	Result vacuum cleaners	Result chocolate	Conclusion
Descriptives μ (σ) n	Group A	2.41 (1.207) n = 44	2.67 (1.297) n = 45	Sales velocity groups B and C have higher likelihood of purchase than the control. Furthermore, p < 0.017* for both "A vs. B" and "A vs. C", so, H1 and H3a are further supported. Effect size in "A vs. C" > "A vs. B" so H3b is supported.
	Group B	3.93 (1.75) n = 45	4.51 (1.805) n = 39	
	Group C	4.56 (1.933) n = 40	5.02 (1.823) n = 44	
Mann–Whitney U tests U, effect size r, p	A vs. B	U = 495.000, r = 0.44 p < 0.001*	U = 379.500, r = 0.49 p < 0.001*	
	A vs. C	U = 333.000, r = 0.54 p < 0.001*	U = 317.000, r = 0.59 p < 0.001*	
	B vs. C	U = 704.500, r = 0.19 p = 0.081	U = 703.500, r = 0.16 p = 0.150	

vs. B comparison, $p < 0.001$*), and also when the higher ranking product has a negative sales velocity (the group A vs. C comparison, $p < 0.001$*). Thus H1 is further supported, bi-directionally. Likewise, H3a is supported. We find that the effect size in the A vs. C negative velocity comparison is larger (0.54 for vacuum cleaners, and 0.59 for chocolate) than the A vs. B positive velocity comparison (0.44 for vacuum cleaners, and 0.49 for chocolate); this supports H3b — given the same perceived relative sales velocity change (as proven in our manipulation check), the sales velocity effect on likelihood of purchase is larger in the negative sales velocity case. We also see from the descriptive statistics that the negative sales velocity has a stronger influence on the likelihood of purchasing product R (for chocolates, $\mu_{\text{group C}} = 5.02 > \mu_{\text{group B}} = 4.51$; likewise for vacuum cleaners $\mu_{\text{group C}} = 4.56 > \mu_{\text{group B}} = 3.93$).

Discussion

Study 3 further supported H1 by showing that both negative and positive sales velocity influences the likelihood of purchase. Furthermore, as per H3a, it showed that a decrease in sales velocity led to a lower likelihood of purchase for that product, and as per H3b it showed that this decrease in sales velocity has a stronger positive effect on the likelihood of purchase of the non-decreasing product than a corresponding increase in sales velocity. This likelihood of purchases in the negative velocity case is also higher than in the positive case.

Overall Discussion

Theoretical Implications

Our results show that increasing sales velocity positively influences the likelihood of purchases (Study 1), and that this result is robust across different products (Study 2). The positive signaling from an improving product was even able to reverse the preference seen in the control group for a higher ranked one — even in the face of the more common sales rank heuristic. These results reveal and address a large gap in OL research, which previously only considered current outcomes arising from others' choices, without factoring in the velocity dimension of these outcomes. We have also extended the general studies in velocity outcomes from Hsee, Abelson, and Salovey (1991) into the context of marketing, and our work builds on the work by Briggs, Landry, and Daugherty (2010), which had shown that velocity metrics of performance is positively correlated with a firms' perception of the providers. We extended these findings by conducting a controlled experiment which proved that there is also an influence on choices, in a context where retailers can use the result for their marketing initiatives.

We further showed that the numerical framing of the sales velocity can strengthen the sales velocity effect on the likelihood of purchases (Study 1), by changing the perception of the rank change. This extends the work on numerosity (Bagchi and Li 2011; Chen and Rao 2007; Kruger and Vargas 2008; Monga and Bagchi 2012; Pandelaere, Briers, and Lembregts 2011; Zhang and Schwarz 2012), and that furthermore, it could be leveraged on non-price metrics like sales velocity to even boost sales. Finally, Study 3 showed that both negative and positive sales velocity influences the likelihood of purchase, and that a product's decrease in sales velocity has a stronger positive effect on the likelihood of purchase of the non-decreasing product than a corresponding increase in sales velocity. Taken together, these studies give researchers a firm ground for future work in using velocity metrics like sales velocity for marketing purposes.

Implications for Consumers

Sales velocity can act as a useful heuristic for consumers in making choices; it has been well established that consumers are often presented with too many choices, suffer from choice overload, and subsequently are less satisfied with their choices (Diehl and Poynor 2010; Scheibehenne, Greifeneder, and Todd 2010). In these situations, consumers are known to resort to heuristics (Oliver 1993) to help them focus their attention on product attributes of importance to them, thus increasing post-choice satisfaction. Since sales velocity presents the less-often bought products, it may be a useful and satisfying

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heuristic for variety seekers who want to try something different from the usual popular and already bought products.

Implications for Retailers

The results demonstrated the impact of the sales velocity metric, which can be easily deployed for both online and offline physical retailers as an additional marketing tool. For example, currently many e-commerce portals use a list of top selling products; similarly, these retailers can also have a list of high sales velocity products (sorted by rank change) to promote mid tail products. Furthermore, we found that alternate numerical representations of sales velocity (i.e. as a % change) leads to a stronger sales velocity effect, when the alternative representation leads to a larger number; this representation can be leveraged to boost the perception of rank change. However, one cautionary note should be considered before deciding on a % change representation; we found afterwards that a % change representation exposes different products in the long tail. Whereas the maximum expected rank change increased when the sales rank of the product got worse (and thus is appropriate for promoting mid-tail to long tail products), we found that except for the #1 product, every product had a chance of exhibiting a large % rank change (in the order of magnitude near 100%) from weekly fluctuations in sales. Thus, which representation is ideal depends on which products the retailer wants to promote.

Retailers can also combine sales velocity with other marketing tools; for example, they could feature targeted products prominently on a website's front page, like a normal advertisement, but justifying the product's presence by stating its sales velocity attribute. Optimization of how to display the sales velocity and validation of its effect on consumer sales and the resultant real-world profitability can also be easily implemented with A/B testing by the retailers; retailers can simply have a group who do not see sales velocity in their apps, and different treatment groups are tested with different sales velocity representations.

The results are also relevant to physical retailers; as shown in the analysis of our one year of receipt data from our European physical grocery retailer partner, sales velocity can be used to promote mid-tail products — which form a large portion of the retailer's revenue. Furthermore, since sales velocity is more suitable to be used for the mid-tail products, it allows retailers to have an alternative and cost-effective promotional vessel other than a series of increasing price cuts for promoting lesser sold goods, which would continually incur an inventory cost otherwise. Having sales velocity as an alternative to price discounts can thus increase revenue. Having sales velocity as another method for promoting products also gives the retailer flexibility. Since many price promotions are negotiated with manufacturers and are planned in advance (Ailawadi et al. 2009; Moreau, Krishna, and Harlam 2001; Murray and Heide 1998), the ability to feature a product without resorting to price negotiations helps the retailer. In the following we discuss some practical recommendations and considerations of our findings.

Sales Velocity Lists Can Complement Sales Rank Lists

We note that the while mid-tail products benefit strongly from sales velocity, products in the head of a long tail tend to be stable and therefore rarely change or increase in rank (and therefore have a low sales velocity). One might therefore ask whether selectively showing sales velocity could be detrimental to the promotion of the popular products.

We posit that since the existing marketing instrument of a "top ten list of products by sales rank" already addresses the products in the head of the long tail, having another instrument that promotes the top ten products by the sales velocity gives the retailer another method to address a previously neglected and different segment of his products. By the very definition of the long tail, since the vast majority of products in fact cannot be the most popular ones (as measured by the current sales rank), it means a much larger pool of products (the majority of products, in fact) can benefit from a sales velocity promotion.

Since the two product lists do not overlap in products and since the two lists draw comparisons between products on two different criteria (one based on OL and the other on sales velocity), we argue that consumers would not perceive the lists as competing. That is, our method does not replace existing marketing measures, but complements them. It provides an alternative marketing instrument to price discounts (which we point out, are also selectively applied to specific products). In the case of our physical grocery retailer partner, mid-tail products consist of 41% of the retailer's revenue, so this is a managerial relevant segment of goods. Operationalized as a list of high velocity mid-tail products (which by definition, consumers do not often buy), sales velocity can encourage variety seeking. Operationalized as a single promoted product, sales velocity can be the attribute highlighted in place of a price discount.

Positive Versus Negative Sales Velocity

One practical matter concerns the positive and negative velocity. Given a period of time, a product can increase in sales rank (positive sales velocity), but also decrease in sales rank (negative sales velocity). We had shown in Study 3 that a product with negative sales velocity would have a low likelihood of purchase. Accordingly, we rather advocate for implementations of sales velocity (such as a top ten list of products) which avoids showing negative information. We recommend against showing sales velocity in every product description embedded as an attribute, since this ensures negative velocity is seen. Furthermore, this is not done at all by practitioners such as Amazon.com; they have always a separate screen devoted only to the top products sorted by either current rank or sales velocity. Accordingly, we would recommend using sales velocity as a promotional tool to selectively promote products, in the place of price discounts, thus saving retailer margin.

Sales Velocity per Category

We would also recommend that the sales rank and velocity be computed within the retailer's product categories. For example, if a consumer browses chocolates, he would get the top ten (or whichever number the retailer chooses) chocolate products sorted by sales velocity, and if he clicks on drinks, he would get the top ten drink products only. The sales rank and velocity of the chocolates would be independent of how drink products perform. By presenting the velocity as an attribute within a category, we avoid the confound that arises from different product categories having different interpurchase times (Leszczyc and Bass 1998; Leszczyc, Sinha, and Sahgal 2004; Rhee and Bell 2002) (and thus, differing influences on the velocity). Furthermore, grouping products by category is in line with consumer mental models of search and choice making (Dellaert and Häubl 2012; Häubl and Trifts 2000); attributes are compared in the context of similar products. This was in fact how we implemented our experiment and how Amazon.com does it with their sales velocity feature.

In-store Feasibility

One question might be whether the ideas in this paper can be implemented in-store, both technologically and also with the buy-in of retailers. Technologically, physical retailers can already operationalize and present sales velocity to consumers via information system artifacts such as mobile phone applications; this has been proven in both research and in practice. In research, in-store recommendation system research (Kowatsch and Maass 2010; Lee and Benbasat 2010; van der Heijden 2006) have already proven the feasibility of such systems; in practice, physical retailers (ex. Walmart) already have apps for their stores where consumers can browse and obtain information about the retailer's products. It therefore would be a simple matter to allow consumers to browse and sort products by the sales velocity.

In terms of actual buy-in from retailers, we have worked with a start-up in developing and deploying a smartphone app for our retail partner that's available for download and contains a top ten list of products sorted by sales velocity and a separate list that contains the products with a high sales rank. The sales rank change is computed from the retailer's PoS data, which we acquire through an interface developed in cooperation with our retail partner's PoS vendor. Therefore, the sales velocity ideas described in this paper are feasible technically and also agreeable with retailers.

Conclusion and Future Research

Although we have shown the robustness of the sales velocity effect across different products and explored its boundaries, future work should test whether the sales velocity effect is diminished in the presence of price and actual monetary loss, similar to the incentive-aligned studies (Miller et al. 2011). This can be achieved by having choices which have real monetary consequences.

We also studied sales velocity's effect with regard to promoting physical products; however it may also be highly effective for services or intangible goods — for example, for vacation packages and destinations or music downloads which are rising in popularity. This should be investigated in future studies.

During our study, we established the effect of sales velocity, operationalizing it as a change over two time periods. The sales velocity can also be measured over multiple time periods, and of interest to consumers might also be the longevity of a positive rank change; for how long has a product been rising? This however, would expand the scope of the research beyond sales velocity, as we now have an implied acceleration or trending component, which was first studied by Hsee, Salovey, and Abelson (1994) in a cognitive psychology experiment. Since our intention was to establish the sales velocity effect in a retail context and to evaluate which type of products a retailer could promote with this method, it was beyond our scope to deal with acceleration measures. We focused on a simple, easy to implement and understandable metric that addresses the mid-tail of sold products. We acknowledge however that an extension of the work by Hsee, Salovey, and Abelson (1994) into the area of sales acceleration would yield further studies and our understanding on the dynamics of sales velocity.

The velocity's interaction effect with the positional rank is also an area of future work — the impact of sales velocity may depend on which rank it rose from and the positions of the final ranks of the products compared. In our paper, we always had an improving brand (rank 100) having a final rank (rank 51) very close to a superior brand (which stayed at rank 50). Future work should investigate further combinations.

Finally, for practitioners, future work may calibrate the effectiveness of sales velocity in a field deployment. With a field deployment, several practical considerations can be evaluated with respect to their real-world effect on purchases and profitability; for example, we suggested that our sales velocity heuristic can be a valuable cue, particularly for space-scarce smartphones. Practitioners can thus examine the tradeoffs between having this cue on display versus having less information in its different visual representations. For example, would a table of "rapid risers" be overall more effective than a table showing both up and down movements? In addition to these visual calibrations, future work of interest to practitioners would be the interaction of sales velocity with aspects such as the persistency of the velocity (how many "weeks on the chart"), which in of itself could be a metric explicitly revealed to consumers to influence their behavior in select product categories (ex. a rapid riser in a stodgy market might be especially valuable and worthy of note). A real-world deployment would also help identify under what conditions would sales velocity complement vs. cannibalize sales of more popular products. These deployments can be easily implemented both online and offline. For a field experiment deployed with an online retailer, similar to the OL experiment by Tucker and Zhang (2011), sales velocity can be a product attribute exogenously revealed on the retailer's e-commerce portal, and as such, it becomes possible to see whether sales velocity influences real-world product choices, and for which products is the influence stronger. For a field experiment with a physical retailer, sales velocity can be potentially operationalized via information systems artifacts such as mobile phones, as an extension to the work on mobile recommendation agents for consumers' in-store choice making (Kowatsch and Maass 2010; Lee and Benbasat 2010; van der Heijden 2006).

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Appendix A. Questions and Measures

A.1. Main Dependent Measures (Used in All Three Studies)

Table A1

						No difference				
Q1	Which offer would you probably buy if you were in the market for this product?	Definitely offer M	1	2	3	4	5	6	7	Definitely offer N

A.2 Manipulation, Attention Checks and Confounding Checks (All Three Studies)

Table A2

						No difference				
Q2	How would you compare the two offers in terms of price?	Offer M much cheaper	1	2	3	4	5	6	7	Offer N much cheaper
Q3	How would you compare the two offers in terms of sales rank change?	Offer M much higher sales rank change	1	2	3	4	5	6	7	Offer N much higher sales rank change
Q4	How would you compare the two offers in terms of current sales rank?	Offer M much higher sales rank	1	2	3	4	5	6	7	Offer N much higher sales rank

A.2.1. Degree of Involvement (Used in Study 1)

Table A2.1

		Strongly disagree			Neutral			Strongly agree
Q5	I am particularly interested in chocolates.	1	2	3	4	5	6	7
Q6	Given my personal interests, chocolates are not very relevant to me.	1	2	3	4	5	6	7
Q7	Overall, I am quite involved when I am purchasing chocolates for personal use.	1	2	3	4	5	6	7
Q8	Overall I am quite involved when I am purchasing chocolates for others.	1	2	3	4	5	6	7

Q9: How different do you consider the two offer descriptions? (1 = "very small", 7 = "very large").

A.2.2 Extent of Hedonism and Frequency of Purchase (Used in Studies 2 and 3)

Question Text: For each statement below, indicate how close to the adjective that you believe best describes your feelings about <Product category>. The more appropriate the adjective seems, the closer you should place your mark to it.

Table A2.2

Q10	Unenjoyable	1	2	3	4	5	6	7	Enjoyable
Q11	Not frequently purchased	1	2	3	4	5	6	7	Frequently purchased

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