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RESEARCH ARTICLE

Herding Among Retail Shoppers: the Case of Television Shopping Network

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Abstract
Herding behavior refers to the behavior of individuals behaving similarly as a group without directions to coordinate. Herding can demonstrate rational characteristics. When consumers believe that others may have private information about a product, they infer unobserved information through other people's behaviors, thereby engaging in similar actions themselves. While rational herding behavior has been found mostly in high involvement environments such as the financial markets, this paper provides evidence that such behavior may also occur in a comparatively lower involvement environment such as retailing. To demonstrate herding behavior and test shoppers' rationality in such, the authors employ a unique dataset from a major TV shopping channel. In this setting, information about other buyers' purchase decisions is only *sometimes* observed by shoppers. Evidence suggests that herding happens among shoppers and the herding behavior appears to exhibit rationality. The authors find that herding effects (1) are stronger when relative price discount is smaller, (2) are more prominent for a product category with less digitalizable attributes, and (3) appear to happen mainly in the earlier part of a sales pitch when shoppers have less information about a product and are more uncertain about their product valuation.

Keywords Herding · Moderators of herding · Retailing · TV shopping

1 Introduction

Herding behavior refers to the behavior of individuals behaving similarly as a group without directions to coordinate. Academic research widely documents the evidence of "herding" behavior, where later arrivers, when making their own decisions, take into account earlier arrivers' behaviors and subsequently make similar choices. In the retailing context, the outcome of herding may result from many reasons. One type of reason is social influence [3, 42, 48]. Such influence can be "verbal" such as word-of-mouth where information about product quality is disseminated through reviews and other forms of user-generated content [11, 15, 28, 39]. It can also be "non-verbal" in the sense that product quality is not revealed directly by previous consumers or users; however, their choices are "silently" observed by others facing similar choices [14].

In the literature, both irrational and rational herding behavior has been documented. In the retailing context, later buyers can "mindlessly" replicate what earlier buyers do, often yielding suboptimal outcomes [38]. However, the literature also finds evidence that herding behavior can be highly rational in nature [19, 47]. The rationale for "rational herding" is that people may have private information over the set of options, and such information is revealed by their choices. Therefore, learning others' choices can help the later decision makers make more informed decisions. For instance, when executives of a public company purchase shares from the open market, other investors can infer from this action that the executives have reasons (unbeknownst to other investors) to believe that the shares are undervalued by the market [6].

A body of literature provides empirical evidence for rational herding in the context of financial markets (e.g., [5, 19]). The scope of such rational herding behavior extends to institutional herding [37], financial analysts issuing securities ratings by following other analysts' opinions [27, 40, 44], and

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microloan funding decisions made by small lenders [26, 47]. However, rational herding has rarely, if ever, been explicitly documented in areas outside of financial markets. This raises an important theoretical question that is of both academic and managerial interest: Is rational herding behavior limited to a high involvement environment such as financial markets, where decision makers are highly incentivized to be rational [19, 46, 47]? Can it also occur in a comparatively lower involvement environment such as retailing?

The goal of our study is to first document herding behavior in a comparatively lower involvement setting outside of the financial markets, then investigate whether the herding appears to be rational or not. To do so, we assemble a unique dataset from a major TV shopping channel that allows us to directly identify and quantify the effect of herding. Our dataset comprises 275 "sales pitches" that were broadcasted between March and April 2014; we manually coded variables from these videos at the minute-by-minute level and combine the video data with the corresponding minute-by-minute sales data. One special feature of these sales pitches is that the viewers can *sometimes* have information on the sales volume through a "sold box" being shown. The "sold box," when shown, displays how many units of the products are sold up to the current minute. Importantly, the "sold box" is available on screen only for some products, and only for certain periods of time during the sales pitches.[1] This quasi-natural experiment setting allows us to examine what happens to subsequent sales when the previous sales volume is known to the potential customers vs. when it is not. It provides a crucial source of variation that allows us to tease apart the role of herding effect vs. "baseline" temporal sales dynamics, and therefore identify what proportion of sales can be attributed to herding behavior.

Conceptually, herding differs from peer effects [10, 23, 35] for the former's lack of direct social contacts. In TV shopping, shoppers do not know each other through the channel. Their purchases are not publicly attributed to individual identities. In contrast, for peer effects to work in full force, the consumption or behavior needs to be public, visible to peers, and exposed to peer pressure due to social conformity. For instance, among studies of peer effects, the subjects in both Sacerdote [35] and Falk and Ichino [23] share a common environment by being either in the same room or being roommates. Similarly, the solar panel adopters in Bollinger and Gillingham [10] share the same zip codes.[2]

Herding resembles and differs from the innovator/imitator new product adoption process theorized by the Bass model [8, 9]. The similarity resides in that innovators (early adopters) and imitators (late adopters) have different product information when they adopt; late adopters are able to observe early adoptions before making their own decisions. In the Bass model, however, the product information aggregation process for late adopters can be quite complicated (a long-term process through word-of-mouth, reviews, various media outlets, and even observations of adoptions from neighbors, family members, colleagues). The herding effect described in this paper occurred during a much shorter time window (minutes vs. years or decades in the Bass model). Perhaps as a result, two key distinctions exist. First, the process by which later adopters acquire product information has a limited time and sources; specifically, it is limited to the early herd's choices and the pitched product characteristics. Furthermore, compared with the focal products in the Bass model, the products on sale at HSN are not necessarily "new" to the marketplace.

Our analyses show that retail shoppers indeed engage in herding behavior. The coefficient estimates from our analysis suggest that for every 100 additional observable previous unit sales in every minute, as much as 2.7 units of additional sales can be attributed to herding effects.[3] To understand whether rationality drives such herding behavior, we provide three pieces of evidence that suggest the herding behavior is indeed "rational" in nature. First, we find that herding effects are moderated by the magnitude of the relative price discounts. Specifically, herding effects are stronger when the relative price discount is *smaller*. This finding is consistent with the hypothesis that later buyers use sales information to infer deal quality: when the sales discount is large, shoppers are more certain that they score a good deal; hence, other shoppers' purchase decision plays a smaller role in affecting their purchase decisions. When the sales discount is small, it is unclear if the deal is attractive. If previous shoppers are willing to purchase the product despite a smaller price discount, they must have "private information" about the deal quality; hence, the herding effect is larger.

Second, we show that herding behavior is more pronounced for product categories with more "intangible" attributes in nature (i.e., cosmetics vs. electronics). Intangible attributes hinder shoppers' ability to evaluate products. For instance, whether or not a perfume smells nice can be subjective; when more people purchase this perfume, the likelihood of it smelling nice becomes higher. Tangible, objective attributes, on the other hand, present a relatively unambiguous situation where the potential buyers can either rank order the attribute specifications (e.g., longer battery life) or have an obvious preference (e.g., someone prefers space gray over silver). Lacking the ability to use tangible attributes to assess product quality, potential buyers are thus more likely to rely

[1] We discuss in detail when the "sold box" is used in the data section.

[2] Note also that herding differs conceptually from "information cascade," which often refers to the phenomenon that consumers ignore private information without having a tangible reason to. In our study, we use the moderating effects on observed sales ("sold box") to infer the rationality of following the herd, *with* a tangible reason.

[3] We use the parameter estimate from Table 3 column (1) row one for this calculation. The actual magnitude of herding effect is context dependent, as we discuss further in the paper.

on past shoppers' choices as a substitute source of information. Therefore, we expect rational herding behavior to be stronger for cosmetic products than for electronics products, a pattern confirmed by our empirical analysis.

Third, we further explore the extent to which herding behavior differs earlier vs. later in a sales pitch. Under the rational herding hypothesis, shoppers may rely more on the indirect information they infer from other shoppers when there is less direct information about a product available. We show that the herding effect is stronger during the earlier part of a sales pitch, which further supports the hypothesis that the herding behavior in our setting is rational in nature.

This study contributes to the literature in the following ways. First, we collect a novel dataset that allows us to link herding to actual sales, instead of using other indirect measures.[4] Because the potential customers in our data can *sometimes* observe actual sales volume for the focal product from earlier buyers, variations in the use of "sold box" allow for the identification of herding effects.

Next, this paper extends the growing literature (e.g., [20]) to explicitly document the phenomenon of rational herding behavior outside of the financial market setting (i.e., in a consumer retail environment), where shoppers' level of involvement in the decision-making process has been shown to be comparatively low [25]. Thus, complementary to prior findings of rational herding behavior in high involvement contexts (e.g., financial analysts, microloan), our evidence suggests that high involvement itself may not be a necessary condition, and it can happen more broadly in comparatively lower buyer involvement environment such as retailing with a sizable effect on demand. Our findings are relevant not only to the context of television shopping networks but also other online settings, a point that we return to in the concluding section.

Finally, we provide explicit evidence supporting the rational herding argument by examining how herding behavior is moderated by perceived deal quality, product categories, and timing. These findings have important implications for retail practitioners in terms of "where" and "when" to leverage herding effects. For instance, when attempting to capitalize on herding effects to boost sales, practitioners should aim at inducing herding early on, when potential customers have less direct information and are less certain of the product valuation. Firms should also consider the nature of the focal product category—sales strategies that attempt to induce herding effects are more useful for categories with intangible attributes such as cosmetics and beauty products, as compared with electronics and office products.

[4] The indirect measures of product popularity used in the literature include the volume of online reviews [16], click-through counts of webpage visits [41], sales ranks published by retailers [16], and potential buyer participations in the auction bidding process [38].

We organize the remainder of the paper as follows. First, we propose four hypotheses based on the theories and empirical findings from previous research. Then, we explain the data structure, our empirical analyses, and results. We conclude with the implications of our research for both academic researchers and practitioners and discuss the caveats and potential future research directions.

2 Theory and Hypotheses

2.1 Herding Behavior in Consumer Retailing

Herding behavior is broadly defined as the alignment of thoughts or behavior of individuals in a group through local interaction and without centralized coordination [34]. As a general phenomenon, herding has been extensively documented in various domains. The scope extends from the evolution of fashion trends to mob violence [34], the role of social influence on individual judgment [18], investors' behavior in financial markets [36], and numerous other settings (see [34] for a review).

Rational herding, a specific type of herding behavior, refers to the phenomenon where, at equilibrium, "agents abandon their own signals and follow others even when they are not really sure that the other person is right" ([7], p. 807). In other words, under rational herding, the tendency of latecomers to follow the "herd" is justified by the assumption that early comers have valuable private information that is not directly observable to subsequent decision makers. Upon observing the herd choice, later decision makers make implicit inferences about the nature of such private information, and as a result align their decisions to be more consistent with the herd than they otherwise would.

Previous academic studies have identified rational herding in financial markets [5, 19, 26, 27, 37, 40, 44, 47]. Speculatively, a main reason why rational herding is often observed in financial markets is that people are often highly engaged, deliberate, and tend to "think slow" [29] in a high-stakes financial decision; thus, they have sufficient mental capacity to engage in the logical reasoning process that characterizes rational herding.

Outside of financial markets, however, empirical research has yet to provide direct evidence on the existence of rational herding. Direct measures of the extent of social influence can be hard to come by; thus, most prior studies that attempt to study the role of social influence on demand typically rely on indirect measurements such as bidding participation in auctions [38], online reviews [16, 22, 49], and the presence of other shoppers in the retail environment [3, 48]. Evidence from online reviews, or "word-of-mouth," also suggest that the volume of reviews is positively associated with product sales [16, 22, 49]. The volume of reviews can be deemed as an

imperfect yet somewhat informative indicator of the popularity of the product. By the same token, Tucker and Zhang [41] use a field experiment to study, in the context of online wedding registries, the effect of popularity information on website click-through counts. They find that revealing popularity information particularly benefits niche products with a narrow appeal, resulting in a larger increase of click-through counts. Other evidence from lab studies and grocery stores show that in a more loosely presented social context, the mere presence of shoppers can influence other shoppers' behaviors [3, 48].

One study by Simonsohn and Ariely [38] examines buyers' participations in auctions on eBay and find evidence of "buyer herding" in the bidding process; specifically, eBay buyers are more likely to bid on auctions with a larger number of previous bidders, among multiple auctions selling comparable or identical merchandise at the same current bidding price.

Given the existing empirical evidence from both lab experiments and field studies, we expect that revealing prior product sales would present an unambiguous signal of the choices of other buyers (the "herd" in the retail context), allowing later shoppers to draw inferences from the herd choices as to whether it is a "good deal." Thus, the higher the number of revealed prior product sales, we expect the more the later sales to be prompted by herding. We hypothesize that:

> **H1**: When shoppers are able to observe previous sales in a retail environment, their likelihood of purchase is positively associated with the observed volume of previous sales.

H1 describes the main effect of herding. If herding exists, we then ask the question of whether such herding is "rational" or "irrational." Specifically, we want to understand further what motivates such herding behavior. Are later shoppers "blindly" following previous buyers' actions without deliberate considerations, or can herding be viewed as a manifestation of a rational decision-making process?

The vast majority of papers that study the role of social influences in retail markets mainly focus on the phenomenon itself and its implications, rather than exploring the issue of the rationality of herding per se [13, 41, 48]. Outside of retailing, in contrast, research on financial markets often find empirical evidence consistent with rational herding [17, 19, 26, 47], where the driving force tends to be rooted in the economic theories on information asymmetry [1, 12]. Importantly, rational herding happens when an agent's information regarding the focal product (or assets) is noisy, making it possible for decision makers to improve decision quality by inferring private information from the herd decisions.

In Simonsohn and Ariely's study of eBay auctions (2008), they argue that, in the context of auctions, herding behavior in buyer bidding is irrational. The rationale is that when buyers bid on an item that has a higher number of previous bids, due to increased competition, at equilibrium, such behavior would lead to a higher final bidding price and/or a lower probability of winning the auction. Thus, by means of following the herd, buyers tend to bid on items with more competitive bids that lead to a lower expected economic surplus.

Given the empirical findings on both rational and irrational herding, we argue that in the retailing context, such seemingly conflicting evidence can be reconciled by examining the "match" between the expertise and nature of the task [2]. When a decision maker faces a task that she is familiar with, she may rely on a set of simplified decision rules that are often based on sound underlying logic and extensive experience [24]. We often refer to these decision rules as heuristics. Tasks such as a security analyst giving an investment rating on a public company, an experienced microloan lender providing loans to borrowers, or a consumer going shopping at a retail store all fall into this category of task familiarity. Herding can be one of these heuristics that are established on the foundation of rationality and tested through experience and reinforcement learning. For example, when a financial analyst is uncertain about her evaluation of an asset, she may rely on the herd—other analysts' evaluation—to provide additional information, a strategy that she may have learned to be beneficial from past experiences [5].

From a task familiarity standpoint, auction differs significantly from what shoppers routinely experience in other retail environments. The mechanism design involved in an auction environment tends to be more complicated than a general retail setting; thus, the irrationality in herding behavior found by Simonsohn and Ariely [38] can potentially be explained by the (relative) inexperience and unfamiliarity of buyers who are still learning about how to bid strategically [43]. Furthermore, the sheer competitive nature of the purchasing process in auctions may trigger irrational emotional responses [21]. In a simpler and more familiar market environment such as consumer retailing, herding can be more deliberate and strategic when consumers are accustomed to the decision-making process. In contrast, for tasks that are unfamiliar or overtaxing (e.g., auctions on eBay), the improper use of heuristics based on experiences from across domains (e.g., from following the herd in a retail store to following the herd on eBay) may turn out to be irrational, as found in the study by Simonsohn and Ariely [38]. Therefore, we reason that for a simple and routine shopping task, herding behavior among buyers is more likely to exhibit rational characteristics.

In this study, we offer three pieces of evidence to support rationality in the use of herding strategy by shoppers from three perspectives: (i) the inferred information of deal attractiveness from herd behavior based on relative price discount, (ii) the informativeness of herd behavior based on product category, and (iii) the amount of available deal information that is not related to herd behavior based on timing. Towards that end, we first examine the moderating role of relative price

discount on herding. We then examine how the magnitude of herding differs for products with more affiliated valuations across the population vs. more private and individualistic valuations. Finally, we look at how the level of herding varies during earlier vs. later in a sales pitch. We discuss the rationale behind each test and formulate hypotheses H2–H4 below.

2.2 Relative Price Discount as a Moderator of Herding Behavior

First, a shopper can infer from the other shoppers' purchase decisions to assess the quality of a deal. Drawn from previous research [47], we operationalize the relative price discount as a key piece of public information for how attractive a deal appears to be on the surface. When a large group of shoppers rush to buy a product that offers a small price discount, the rational inference could be that something other than the price discount itself (that is not known by the focal shopper but can be private information of other shoppers) must make the product attractive. Since rational herding is driven by inferring private signals in herd behavior, a high level of herd buying combined with a low relative price discount should imply positive inferred information about deal quality from the herd, therefore further increasing herding effect on later buyers. Informally, this line of argument is consistent with the thought process that "if so many people are rushing to buy the product even at a minimal discount, there must be something really good about the deal that I do not directly see. Therefore, I should also buy." We formalize the above arguments by framing the negative moderating effect of price discount on herding as follows:

> **H2**: Relative price discount negatively moderates the herding effect demonstrated among shoppers.

H2 states that the larger the relative price discount, the smaller the magnitude of herding. Note that the focus in this case is not the main effect of price discount on demand. Clearly, we expect the main effect to be positive, as a larger price discount leads to higher demand. Instead, we care about how relative price discount *moderates* the magnitude of herding effect. That means the key coefficient estimate is on the interaction of relative price discount and observed previous sales volume, and it is expected to be negative.

2.3 Product Category as a Moderator of Herding Behavior

The key driver for the moderating effect described in H2 comes from the inference of private information from the herd behavior. Next, we look at how tangible vs. intangible product attributes affect the effect of herding. We then ask that under what circumstances buyers are more inclined to rely on inferred information (as opposed to direct information about the product) for purchase decisions? For the two product categories in our data, beauty and cosmetics vs. electronics, we follow the frameworks developed in the literature (e.g., [30]) and differentiate products by the nature of their features. Specifically, product features are either more tangible to digitalization, where one can obtain a comprehensive understanding of the product features by reading the description or simply knowing the product name itself (products with "digital attributes"), or more intangible and difficult to describe in words (products with "non-digital attributes"). In our data, electronic products fall into the former category, and beauty and cosmetics fall in the latter.

With "digital attributes," there is more direct information about a product available by nature. With "non-digital attributes," even a product demonstration, such as those done by TV shopping network hosts and nowadays on webpages, may not provide sufficient tangible information. Hence, a focal buyer is more likely to use indirect information from other buyers to make inferences during the decision-making process when the product has more "non-digital" attributes. Therefore, we hypothesize that the herding effect described in H1 would vary by the nature of product categories and demonstrate different effect strengths for different product categories. That means we expect the magnitude of herding effect to be larger for beauty and health products, compared with electronics. This interaction between product category and herding effect is formally hypothesized in H3 below.

> **H3**: The herding effect is more prominent for product categories with more intangible and non-digital attributes.

2.4 Timing as a Moderator of Herding Behavior

Finally, examining the effect size of herding behavior during different times of a sales pitch may help further shed light on the rationality of herding behavior. When a shopper rationally engages in herding, she makes inferences about other shoppers' revealed private information through their purchase decisions. Therefore, the more uncertain a focal shopper is about product evaluation, the more she can potentially gain from herding. During a sales pitch where product information is relayed sequentially to the viewer during the course of several minutes, the "amount" of product information that viewers have at any given point in time is governed by the "relative time" into the sales pitch. The further into a sales pitch, the more product information is revealed to the viewer. Interestingly, consistent with our reasoning, previous research on career development suggests that earlier during the career, managers and financial analysts alike, for lack of private information themselves, are more

inclined to herd [4, 27, 31]. Therefore, we hypothesize that:

> **H4**: Shoppers exhibit stronger herding behavior earlier during a sales pitch.

3 Data and Empirical Analysis

3.1 Data

We collected our dataset from a major TV shopping network. The TV programs comprise a series of separate sales pitches. During each sales pitch, one or two hosts promote a product or a bundle of products by demonstrating how it works, explaining its functionality, effectiveness, esthetics, etc. Program viewers call a toll-free number listed on the screen if they want to purchase the promoted products. Each sales pitch receives a designated time segment that lasts anywhere from a few minutes to approximately an hour. In total, our dataset comprises live recordings of 275 sales pitches that were broadcasted between March and April 2014. These pitches were broadcasted at various times during the day. Figure 1 illustrates two screenshots from a sales pitch. During a sales pitch, some information about the product is always displayed on the screen, including the product number, name/description, price, and the 1-800 toll-free number (see the top panel of Fig. 1). The variable of interest—cumulative sales volume thus far—is only shown to the audience for some portion of a sales pitch, and there is no set time for when it is shown.[5] The audience must be able to observe how many units of the product have been sold for herding to occur. As shown in the bottom panel of Fig. 1, the audience can see "303 sold" on the bottom right corner on the screen (i.e., the "sold box" is displayed), which indicates that a total of 303 units of the focal product have been purchased by other viewers up to that point. The variations in the presence or absence of items sold information on the screen are essential to our identification strategy. The sales volume (while not observed by other shoppers) reflects the intrinsic (non-herding) attractiveness of the focal item on sale. Had the items sold information always been on display (and hence always observed by the viewers), we would not have been able to cleanly separate how much of the subsequent demand is generated by the product itself, and how much is due to the herding effect.

In addition to the minute-by-minute level variable of the sales volume shown in the "sold box," we also code the minute-by-minute unit sales and the number of buyers (for additional robustness checks discussed later). For each product on sale, we have a detailed description of the product: we code the suggested retail price, the actual price of the product for the sales pitch, and construct a variable that is the percentage of price discounts. In addition, we record the length of each sales pitch and create a dummy variable for the product category (electronics vs. health and beauty). For all but the sales information, we watched each video file and manually coded them, including the incidence and time period when the "sold box" is shown on screen.[6] Table 1 summarizes the variables we extracted from the sales pitches at the pitch-minute level.

For illustrative purposes, Fig. 2 demonstrates the minute-by-minute unit sales trend of Visionnaire Blur by Lancôme, a skincare product that intends to help blur facial wrinkles or imperfections. The product has a listed retail price of $55 and was on sale at the same price (i.e., no price discount) on a separate retail channel owned by the TV shopping network. As can be seen in Fig. 2, this particular sales pitch lasted a total of 11 min. At the sixth minute, information about the previous units sold, in the form of the aforementioned "sold box," started to appear on the screen and lasted through the tenth minute, then the "sold box" was taken off the screen. Figure 2 appears to show a small increase in unit sales when the "sold box" appeared at the sixth minute. Throughout the time period when units' sold information is shown, we observe an uptick in product sales. Though non-conclusive, the illustration provides a glimpse of what herding response may look like. Of course, this single example cannot represent all the sales pitches, as what we observe in this specific occasion can be coincidental. Next, we conduct a systematic empirical analysis to assess the extent of herding behavior.

3.2 Empirical Analysis

We model the product unit sales y_{it} for pitch i ($i = 1, \ldots, I$) during minute t_i ($t_i = 1, \ldots, T_i$, referred to as t hereafter[7]) as a function of the observed lag cumulative sales in the "sold box", Y_{it-1}^{Obs} (which captures herding behavior), and a set of controls of additional pitch/time specific covariates (Eq. 1)[8]:

$$y_{it} = \phi_1 \cdot Y_{it-1}^{\text{Obs}} + \phi_2 \cdot Y_{it-1} + \beta_1 \cdot \text{NORMTIME}_{it} + \theta_i + \varepsilon_{it} \quad (1)$$

[5] At any point of time during a sales pitch, the sales hosts control when to display and take off the "sales box" that shows how many units of products have been sold thus far.

[6] The database from the TV shopping network does not contain "sold box" information, an indication of the non-strategic role of the "sold box" in the TV shopping programs.

[7] For ease of reading, we suppress the subscript i for all future references of t_i, with the understanding that T_i, the total length of pitch i, is pitch specific.

[8] The model described in Eq. 1 is a dynamic model with fixed effects, which can lead to biases in estimates under certain sample size conditions [33]. We replicated the analysis using the SAS procedure PROC Panel, which addresses such potential biases. The results remain substantively consistent.

Fig. 1 Screenshots of a sales pitch

where Y_{it-1}^{Obs} is the sales volume displayed in the "sold box"; it takes the value of the lag cumulative sales volume Y_{it-1} and the value of 0 for any minute that it is not shown. Therefore, the coefficient ϕ_1 captures the average effect of herding behavior (when all sales pitches and time are treated equally). Hypothesis H1 is supported if ϕ_1 is positive and statistically significant. In addition, we include the lag cumulative sales volume, Y_{it-1}, to control for the "baseline" non-herding sales dynamics where product sales may be related to lag cumulative sales. Importantly, including both Y_{it-1}^{Obs} and Y_{it-1} is crucial for a clean identification of herding behavior: Y_{it-1} controls for the temporal sales dynamics for each pitch and ensures that the effect of Y_{it-1}^{Obs} consistently reflects the outcome from herding itself, above and beyond baseline sales dynamics.

The normalized time, NORMTIME_{it}, is a continuous variable bounded between 0 and 1. We define $\text{NORMTIME}_{it} = 0$ at the beginning of pitch i; and $\text{NORMTIME}_{it} = 1$ at the end. For every minute in between, we interpolate the time linearly to normalize it between 0 and 1. For example, for a sales pitch that lasts 10 min, $\text{NORMTIME}_{it} = 0.3$ for the third minute. In this study, NORMTIME_{it} serves as a control for the natural temporal dynamics that may occur during the sales pitches, which often peaks towards the latter of the time segment.

We include a pitch-level fixed-effect θ_i to account for other pitch-level variations that also affect demand. Once θ_i is included, the main effects of any time invariant pitch-level covariates are absorbed by θ_i, hence are not separately included in Eq. 1.[9] ε_{it} denotes the unobserved random error.

Table 2 reports the regression results for the main effect. In support of H1, column (1) suggests that showing sales information to shoppers increases sales ($\phi_1 = 0.004$, $p < 0.01$). On average, per minute demand increases by 4 units when observed sales volume increases by 1000. This suggests that shoppers appear to take other shoppers' purchase actions into consideration in the decision-making process, and as a result, we observe herding behavior. Column (2) replicates the findings from column (1) by using the number of buyers as dependent variable.

[9] However, a set of time-invariable variables Z_i (e.g., relative price discount as hypothesized in H2) are useful when examining their moderating effect on herding (S_{it}).

Table 1 Summary statistics by sales pitch-minute

	Observations	Mean	Std. dev.	Min	Max
Variables					
Unit sales (y_{it})	4808	34.21	49.25	0.00	603.00
# of buyers (NB_{it})	4808	33.49	47.65	0.00	577.00
Sold box display of sales volume (Y_{it-1}^{Obs})	4808	246.55	580.92	0.00	6495.00
Lag cumulative unit sales (Y_{it-1})	4808	313.14	597.24	0.00	6986.00
% Discount ($DISCOUNT_i$)	4808	0.31	0.22	0.00	0.79
Length of show	4808	23.87	13.39	4.00	62.00
Dummy (product category) ($BEAUTY_i$) (1 = health and beauty; 0 = electronics)	4808	0.55	0.50	0.00	1.00
Health and beauty products					
Unit sales (y_{it})	2640	49.30	59.36	0.00	603.00
# of buyers (NB_{it})	2640	48.43	57.43	0.00	577.00
Sold box display of sales volume (Y_{it-1}^{Obs})	2640	385.43	733.18	0.00	6495.00
Lag cumulative unit sales (Y_{it-1})	2640	454.61	750.63	0.00	6986.00
% Discount ($DISCOUNT_i$)	2640	0.31	0.24	0.00	0.79
Length of show	2640	21.76	12.14	4.00	48.00
Electronics products					
Unit sales (y_{it})	2168	15.84	21.80	0.00	217.00
# of buyers (NB_{it})	2168	15.30	20.41	0.00	213.00
Sold box display of sales volume (Y_{it-1}^{Obs})	2168	77.45	204.57	0.00	2069.00
Lag cumulative unit sales (Y_{it-1})	2168	140.88	225.89	0.00	2181.00
% Discount ($DISCOUNT_i$)	2168	0.31	0.19	0.00	0.62
Length of show	2168	26.43	14.36	8.00	62.00

Additionally, we find the lag cumulative sales (Y_{it-1}), which controls for the baseline sales dynamics, to be positive and significant (Table 2, Column 1: $\phi_2 = 0.007$, $p < 0.01$). It demonstrates face validity as one would expect in a natural sales sequence, where products with more sales earlier tend to also attract more sales later. The control variable $NORMTIME_{it}$ is statistically significant ($p < 0.01$); the sign of the variable, as expected, indicates an upward sales trend over time.

3.3 Evidence on Rational Herding

Table 2 documents the existence of herding behavior in our retail environment. On average, sales get an extra boost when shoppers can observe information on previous sales volume through the display of "sold box"; the higher the sales volume from previous shoppers, the larger the sales boost. Next, we investigate if there is evidence suggesting the observed herding behavior to be rational in nature.

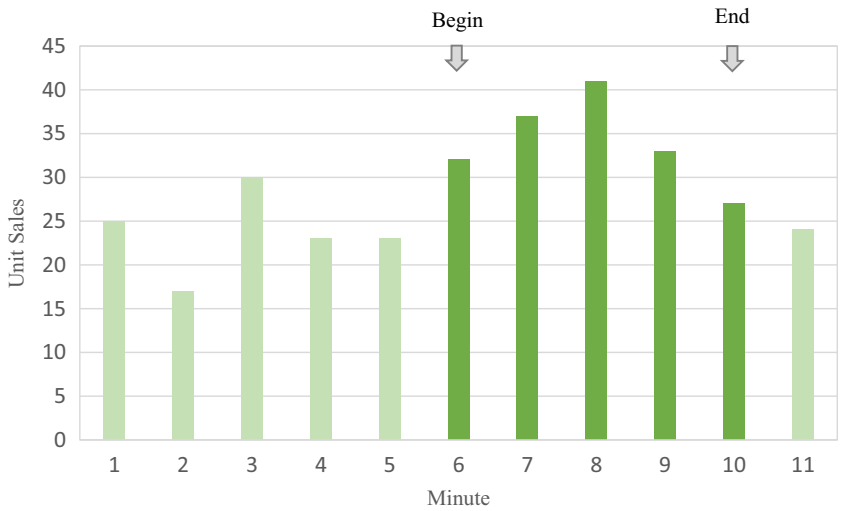

Fig. 2 Minute-by-minute sales of Lancôme Visionnaire Blur. "Begin" means the time by which information about "previous units sold" first appears on-screen. "End" indicates the time by which such information is taken off-screen

Table 2 Sold box sales information and shopper demand—main herding effect

Dependent variable ➔	(1) Unit sales (y_{it})	(2) # Buyers (NB_{it})
Sold box display of sales volume (Y_{it-1}^{Obs})	0.004*** (0.002)	0.004** (0.002)
Lag cumulative sales (Y_{it-1})	0.007*** (0.002)	0.007*** (0.002)
Normalized time ($NORMTIME_{it}$)	36.035*** (1.457)	35.302*** (1.418)
With pitch specific fixed effect	Yes	Yes
# observations	4808	4808
Adjusted R^2	0.777	0.774
−2 residual log-likelihood	42,157	41,908

Unit of observation is the sales pitch-minute. Fixed-effect linear regressions are shown. Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$

As discussed earlier, we take three steps to investigate rationality in shoppers' herding behavior that corresponds to hypotheses H2–H4. First, we investigate how relative price discount moderates the magnitude of herding effect. Next, we examine how product category further separates the effect of herding. And last, we look at how herding behavior differs across time during a sales pitch.

To do so, it is necessary to first introduce a set of time-invariant variables Z_i. Z_i includes two variables: relative price discount ($DISCOUNT_i$) and a dummy variable indicating the electronics product category ($ETRONICS_i$). $DISCOUNT_i$ is the relative price discount, in percentage terms, during sales pitch i:

$$DISCOUNT_i = \frac{\text{Listed Retail Price}_i - \text{Actual Price}_i}{\text{Listed Retail Price}_i}$$

It is always non-negative: higher value of $DISCOUNT_i$ indicates a deeper relative price discount. Finally, $ETRONICS_i$ is a binary variable that captures the two categories of products that we have in our dataset. $ETRONICS_i = 1$ for products belonging to the electronics category, and $ETRONICS_i = 0$ for products belonging to the health and beauty category. All the sales pitches in our data sample sell a product in either of the categories. The dummy variable created for product categories reflects the nature of the products, where electronics are predominantly characterized by digitalizable product attributes, while health and beauty products are often characterized by non-digitalizable attributes.

3.3.1 The Moderating Effect of Relative Price Discount

To test H2, we expand Eq. 1 by including the interaction between relative price discount ($DISCOUNT_i$) and "sold box" sales volume (Y_{it-1}^{Obs}) as an additional independent variable in the analysis. Although not our primary parameter of interest, we include the interaction between retail price and "sold box" sales as an additional control. We specify this analysis in Eq. 2.

$$y_{it} = \phi_1 \cdot Y_{it-1}^{Obs} + \phi_2 \cdot Y_{it-1} + \beta_1 \cdot NORMTIME_{it} + \beta_2 \cdot Y_{it-1}^{Obs} \times DISCOUNT_i + \theta_i + \varepsilon_{it} \quad (2)$$

Table 3 presents the results for estimating the model described by Eq. 2. We show evidence of a negative moderation: the smaller the relative price discount, the larger the impact of previous sales volume on subsequent sales (column 1: $\beta_2 = -0.051$, $p < 0.001$), supporting H2. The herding effect with a specific level of relative price discount is given jointly by ϕ_1 and β_2. In Table 3 column (1), ϕ_1 is positive and significant, and β_2 is negative and significant. These estimates imply that, given the same level of sales information, the larger the relative discount, the smaller the impact of herding. To put these estimates into perspective, for a sales pitch with no price discount, every additional 1000 units of sales observed by shoppers generate 27 additional units of sales in a minute, on average. For a sales pitch with a large discount, say 50% off the retail price, giving shoppers information on sales volume does very little in promoting additional sales.

These estimates are consistent with a rational shopper's behavior: heavy discount provides direct information of a great deal; hence, she needs to consider very little additional indirect product information when making a purchase decision (so herding plays a minimal role). When the relative price discount is small, direct information alone is not enough in converting to a purchase; shoppers depend more heavily on other indirect information such as previous sales information for private signals. In this case, large sales volume indicates a positive private signal. This finding suggests that the

Table 3 Relative price discount moderates herding effect

Dependent variable ➔	(1) Unit sales (y_{it})	(2) # Buyers (NB_{it})
Sold box display of sales volume (Y_{it-1}^{Obs})	0.027*** (0.003)	0.025*** (0.002)
Lag cumulative sales (Y_{it-1})	0.011*** (0.002)	0.010*** (0.002)
Normalized time ($NORMTIME_{it}$)	32.918*** (1.459)	32.365*** (1.421)
Sold box sales (Y_{it-1}^{Obs}) × % discount ($DISCOUNT_i$)	−0.051*** (0.004)	−0.048*** (0.004)
With pitch specific fixed effect	Yes	Yes
# observations	4808	4808
Adjusted R^2	0.784	0.781
−2 residual log-likelihood	42,026	41,786

Unit of observation is the sales pitch-minute. Fixed-effect linear regressions are shown

Standard errors in parentheses ***$p < 0.01$

herding behavior is deliberate and strategic in nature, implying that the shoppers engage in a rational decision-making process, and herding can be viewed as a manifestation of rational behavior. As a robustness check, column (2) in Table 3 uses the number of buyers as an alternative dependent variable, providing additional evidence for robustness.

Among other estimates in column (1), the lag cumulative sales (Y_{it-1}), which controls for the baseline sales dynamics, stays positive and significant ($\phi_2 = 0.011$, $p < 0.01$). The control variable $NORMTIME_{it}$ is consistent with the estimates reported in Table 2.

3.3.2 The Moderating Effect of Electronics Category

To test H3, we further incorporate $ETRONICS_i$ in an interaction with "sold box" sales volume. Specifically, we estimate the moderating effect of product category using the following model:

$$y_{it} = \phi_1 \cdot Y_{it-1}^{Obs} + \phi_2 \cdot Y_{it-1} + \beta_1 \cdot NORMTIME_{it} + \beta_2 \cdot Y_{it-1}^{Obs} \times DISCOUNT_i + \beta_3 \cdot Y_{it-1}^{Obs} \times ETRONICS_i + \theta_i + \varepsilon_{it} \quad (3)$$

Table 4 presents the estimated results, mirroring the structure of Table 2 and Table 3. In column (1), the estimate for Y_{it-1}^{Obs} is positive and significant ($\phi_1 = 0.023$, $p < 0.01$), and the estimate for $Y_{it-1}^{Obs} \times ETRONICS_i$ is negative and significant ($\beta_3 = -0.008$, $p < 0.01$), supporting H3. ϕ_1 reflects the main effects of herding for health and beauty products, and $\phi_1 + \beta_3$ together reflects the herding effect for electronics products. This means, all else held equal, when visible to the customers, previous sales information has a larger impact on a focal customer's purchase decision when she is considering health and beauty compared with electronic products. Column (2) in Table 4 shows robustness to this finding with a different dependent variable.

Table 4 Electronics product category moderates herding effect

Dependent variable ➔	(1) Unit sales (y_{it})	(2) # Buyers (NB_{it})
Sold box display of sales volume (Y_{it-1}^{Obs})	0.023*** (0.003)	0.027*** (0.003)
Lag cumulative sales (Y_{it-1})	0.010*** (0.002)	0.010*** (0.002)
Normalized time ($NORMTIME_{it}$)	33.624*** (1.487)	33.352*** (1.447)
Sold box sales (Y_{it-1}^{Obs}) × % discount ($DISCOUNT_i$)	−0.053*** (0.004)	−0.051*** (0.004)
Sold box sales (Y_{it-1}^{Obs}) × category dummy ($ETRONICS_i$)	−0.008*** (0.003)	−0.012*** (0.003)
With pitch specific fixed-effect	Yes	Yes
# observations	4808	4808
Adjusted R^2	0.784	0.781
−2 residual log-likelihood	42,029	41,783

Unit of observation is the sales pitch-minute. Fixed-effect linear regressions are shown

Standard errors in parentheses ***$p < 0.01$

The estimated coefficients for the control variables in column (1) are overall consistent with those reported in Table 3. Most notably, the moderating effect of relative price discount on "sold box" sales stays negative and significant ($\beta_2 = -0.047$, $p < 0.01$), consistently supporting H2.

3.3.3 Early vs. Late

Lastly, we explore the difference of herding effect between the early and late period of a sales pitch by including an interaction term of "sold box" sales volume and the normalized time variable (NORMTIME_{it}). We specify the analysis in Eq. 4.

$$y_{it} = \phi_1 \cdot Y^{\text{Obs}}_{it-1} + \phi_2 \cdot Y_{it-1} + \beta_1 \cdot \text{NORMTIME}_{it} + \beta_2 \cdot Y^{\text{Obs}}_{it-1} \times \text{DISCOUNT}_i + \beta_3 \cdot Y^{\text{Obs}}_{it-1} \times \text{ETRONICS}_i + \beta_4 \cdot Y^{\text{Obs}}_{it-1} \times \text{NORMTIME}_{it} + \theta_i + \varepsilon_{it} \quad (4)$$

In column (1), Table 5 shows that NORMTIME_{it} negatively moderates the herding effect ($\beta_4 = -0.069$, $p < 0.01$), suggesting early during the sales pitches, the herding effect is larger than later. The results confirm hypothesis H4 and provide an additional piece of evidence that the observation of herding is likely to be rational in nature. Column (2) in Table 5 shows robustness to this finding using a different dependent variable.

The estimated coefficients for the control variables in column (1) are substantively consistent with those reported in Table 2, Table 3, and Table 4. Most notably, the moderating effect of relative price discount on herding effect stays negative and significant ($\beta_2 = -0.052$, $p < 0.01$), consistently supporting H2. The moderating effect of the electronics category on herding effect stays negative and significant ($\beta_3 = -0.008$, $p < 0.01$), consistently supporting H3.

To summarize, the above analyses (Eqs. 2–4) investigate the rationality of herding effect from three perspectives: (i) the inferred information of deal attractiveness from herd behavior (based on the moderating effect of relative price discount), (ii) the informativeness of the inferred attractiveness for a late arriver (based on the moderating effect of the electronics category), and (iii) the alternative source of information related to deal attractiveness other than herd behavior (based on the extent of herding earlier vs. later in a sales pitch). All the analyses suggest that herding is a manifestation of shoppers' rational decision-making process—when previous sales volume contains potential private information about a product, they are used by other shoppers to make the purchase decision; the more/better information it may contain, the more it impacts subsequent demand.

3.4 Endogeneity

We acknowledge that there is a potential issue of endogeneity in our analysis, if the display of the "sold box" is strategic. Specifically, if the "sold box" is more likely to be strategically shown when the cumulative sales are high, it could potentially lead to bias in the estimated herding effect. We present several pieces of evidence and argue that our findings are not explained by endogeneity.

First, when we acquired the data from the TV shopping network, we had the opportunity to speak to the manager in charge of research. She indicated that the display of unit sales on screen was not a "strategic decision" in the sense that there was no internal "optimization" process to control whether or when to show such information. The hosts rely on their subjective "gut feeling" at the moment to decide whether and when to show the "sold box" information, but there is no direct feedback to inform them at any point during a sales

Table 5 The herding effect is more prominent at earlier times

	(1)	(2)
Dependent variable ➔	Unit sales (y_{it})	# Buyers (NB_{it})
Sold box display of sales volume (Y^{Obs}_{it-1})	0.084*** (0.004)	0.083*** (0.004)
Lag cumulative sales (Y_{it-1})	0.017*** (0.002)	0.017*** (0.002)
Normalized time (NORMTIME_{it})	31.614*** (1.445)	31.365*** (1.405)
Sold box sales (Y^{Obs}_{it-1}) × % discount (DISCOUNT_i)	−0.052*** (0.004)	−0.049*** (0.004)
Sold box sales (Y^{Obs}_{it-1}) × category dummy (ETRONICS_i)	−0.008*** (0.003)	−0.012*** (0.003)
Sold box sales (Y^{Obs}_{it-1}) × normalized time (NORMTIME_{it})	−0.069*** (0.004)	−0.068*** (0.004)
With pitch specific fixed-effect	Yes	Yes
# observations	4808	4808
Adjusted R^2	0.797	0.795
−2 Residual Log-Likelihood	41,751	41,496

Unit of observation is the sales pitch-minute. Fixed-effect linear regressions are shown

Standard errors in parentheses ***$p < 0.01$

pitch if their action leads to an increase in sales.[10] In fact, once a segment of the show started, the hosts, who were in control of displaying the "sold box," were not in direct communication with the sales team and were not given any minute-by-minute sales updates. Given the lack of pertinent sales information, the strategic placement of the "sold box" seems implausible.

Additionally, the summary statistics in Table 1 is consistent with the notion that the hosts, uninformed of product sales volume, were not placing the "sold box" strategically. As a form of observational learning, herding is driven by the sales volume from previous buyers. Therefore, to encourage herding, a host should take advantage of the "sold box" when the sales volume is relatively high. This is however not the case. In Table 1, the average "sold box" display of sales volume is 246.55, while the average lag cumulative unit sales (observed and unobserved) is higher at 313.14. The relative magnitude of the average "sold box" display of sales volume vs. lag cumulative unit sales is also true for both product categories—health and beauty products (285.43 vs. 454.61) and electronic products (77.45 vs. 140.88).

Furthermore, the possible endogeneity does not consistently explain the difference of herding effect in our estimate across the different levels of price discounts, the differences across product categories, and the differences across time. Thus, overall, while we cannot with certainty rule out any role that endogeneity may play in our analysis (with regard to the placement of the "sold box"), evidence from the field and data both suggest that estimated bias due to endogeneity is not a primary concern.

4 Conclusion

In this paper, we examine what happens to subsequent demand when previous sales volume is revealed to shoppers in a quasi-experiment using a novel dataset we collected from the TV shopping industry. We first document that herding behavior exists in the retail environment and then provides three pieces of evidence that suggest the observed herding is rational in nature.

Overall, our findings suggest that the shopper herding we document in the retail context appears to be the manifestation of a deliberate decision-making process. We find that when shoppers have a less direct signal on the quality of a deal (e.g., a small discount on a product), when the other buyers' valuations of the product are less informative/relevant (e.g., health and beauty products with more subjective attributes such as style and smell), or when they have less information on the deal or product itself (i.e., earlier during a sales pitch), they rely on previous shoppers' purchase decisions more. Conversely, they rely less heavily on the previous sales volume (and the private information implied by these previous purchasing decisions) when they have a more direct signal on the quality of a deal, when the other buyers' valuations of the product are more informative (e.g., cosmetics and beauty products with non-digitalizable attributes such as smell), or when they have more information about a product. All the evidence supports the argument that the herding behavior is rational: shoppers only allow other shoppers' actions to affect theirs if these actions potentially contain useful information. The more or better quality of the indirect information, the larger the impact of the "herding" we observe.

We contribute to the literature by providing evidence on rational herding outside of the high involvement environments such as the financial markets. We reconcile the findings on both rational and irrational herding in the literature by conjecturing that whether or not shoppers can use the information from other shoppers' actions effectively depends on the match between the expertise and nature of the task. Therefore, although our study uses data from the context of TV shopping, the findings can be generalized into a broader set of industries and decision-making framework. Future research may look at other potential moderating factors. For instance, information asymmetry also exists in the markets with small vendors (e.g., on eBay or Amazon third party sellers). On eBay, for example, products being sold are often non-standard, unbranded, used, open box, or coming through an unofficial distribution network. For buyers, this creates an ambiguous situation of incomplete information concerning the condition or quality of the products, a situation where the buyers can benefit from inferred private information through herding (e.g., the number of previous units sold). In fact, both Amazon.com ("Today's Deals") and eBay (both on product sales pages and in promotion emails) explicitly reveal the unit sales information in a manner that is very similar to the "sold box" studied in this research. Taking this one step further, our results here may be relevant to other online settings as well. For instance, currently, HSN online has a small video window on each of their product pages showing a host presenting a product; it may be beneficial to leverage the strategy of adding a "sold box" there as well to encourage herding behavior. In another context, in many Asian countries, there is a growing trend where an "internet celebrity" would perform various routines in front of a webcam while seeking voluntary "donations" from the viewers to support their shows; in that context, the host would often dynamically update the number of people who have tipped (and the amount they have contributed), which is in the same spirit as the "sold box" discussed here; the results found in this paper may apply to that context as well.

[10] We acknowledge that there can still be a relationship between sales and the use of "sold box," as the host may rely on their prior experience and/or "hunches" to display the "sold box" strategically.

Our results also carry important managerial implications. First, our findings imply that in the retail environment (or any environment that people are familiar with the decision task or have expertise in), when making purchase decisions, shoppers consider the total mix of available information, direct or indirect. As a result, when direct information is lacking, firms can supplement with indirect information such as previous sales volume to help increase demand. Second, since the magnitude of herding effects appears to be context dependent, revealing product sales information can significantly increase product sales when used appropriately. More specifically, the differentiation between rational and irrational herding addressed in this paper matters because of its implications for the retailer, as the strategies that retailers may use depend crucially on the nature of such herding behavior. If herding is irrational in nature, retailers may want to publicize "herding" information whenever the number of prior purchases is sufficiently large. However, if herding is rational in nature, retailers may want to reveal such information more selectively (e.g., only on products with low discounts), to avoid over-using such signals.

There are several limitations to this research, which also points to some promising directions for future research. First, in our sales data, the identities of buyers are not available. Therefore, we cannot directly investigate the motives that drive herding from the perspective of the individual buyer. Although this is a common caveat among secondary data studies of herding behavior, a more granular, individual-level data can potentially allow us to obtain deeper insights.

Second, in this paper, we have only extract information regarding the "sold box" from the sales pitch videos but have largely ignored otherwise video/audio information in the sales pitch. In future research, one may want to extract additional video (e.g., the appearance of the host) and audio (voice characteristic of the host) information from sale pitches using readily available software systems, and explore the extent to which such video and audio features are associated with minute-by-minute sales, in the same spirit as prior studies such as Lu, Li, and Ding [32].

Third, shoppers at a TV shopping network may not be a representative sample of the general population, as the buyer demographics tend to be disproportionately female [45], among other differences. Our findings can be strengthened with further analyses from a wider spectrum of data sources. We argue, however, that since our focus on the rationality of herding is not particularly sensitive to a particular demographic segment of buyers, the insights obtained in this study should be generalizable to other shopping environments.

Fourth, our data covers only a relatively short time window of 2 months (between March and April 2014). It would be valuable to collect additional data with a longer time span combined with individual buyer identities as discussed earlier, which would allow us to investigate the long-term dynamics of herding behavior and possibly the evolution of herding through learning. In particular, such longitudinal data would allow us to study the "origin" of herding, i.e., how new buyers may learn to follow the herd and gradually optimize their strategic moves with the herd. We believe this is a fruitful area of study for future research.

Furthermore, the sales pitches at the TV shopping network happen sequentially, with only one live sales pitch going on at a specific point of time. The "sequential" nature of sales pitches allows us to limit the existence of potential confounding factors in our analysis of herding behavior. It differs from a more general retail environment where multiple substitutes may be sold at the same time, thereby potentially distracting later shoppers from focusing on the behavior of a single herd. Concurrent selling events may cause the herds to "diverge," i.e., spread out across substitute products, or alternatively, to "converge" on a subset of the products, which may increase herding effect on certain products while depleting herding effect on the others. Between the two possibilities, we hypothesize that "converging" herds are more likely, as it resembles an evolutionary natural selection process. In a social context where deviating from the herd and making a poor unpopular choice can be particularly embarrassing, such herding behavior would increase the uncertainty in making an optimal choice, as the possibilities of the herd being "very right" or "very wrong" both increase.

Last, in our data sample, the "sold box" was shown on the screen during approximately 42% of the time. We do not believe our results can be extrapolated to the extreme situation where the "sold box" is always displayed on the screen. We hypothesize that there is a natural threshold where buyers become insensitive to "sold box" information when it becomes omnipresent. With our data, however, we are unable to pinpoint such an optimal portion of time to maximize herding effect. A field experiment can potentially answer this question.

Nevertheless, we believe our results show evidence of rational herding in the retailing context and shed light on the mechanism of how consumers use the complete set of available information to make decisions. In particular, we show that under rational decision-making, herding appears to be stronger when consumers have higher uncertainty, and/or less information about the quality of a deal or product, hence assign more weight on others' actions in an attempt to extract information or private signals.

References

1. Akerlof GA (1970) The market for 'lemons': quality uncertainty and the market mechanism. Q J Econ 84(3):488–500
2. Alba JW, Wesley Hutchinson J (1987) Dimensions of consumer expertise. J Consum Res 13(4):411–454

3. Argo JJ, Dahl DW, Manchanda RV (2005) The influence of a mere social presence in a retail context. J Consum Res 32(2):207–212
4. Avery CN, Chevalier JA (1999) Herding over the career. Econ Lett 63(3):327–333
5. Avery C, Zemsky P (1998) Multidimensional uncertainty and herd behavior in financial markets. Am Econ Rev 88(4):724–748
6. Babenko I, Tserlukevich Y, Vedrashko A (2012) The credibility of open market share repurchase signaling. J Financ Quant Anal 47(5): 1059–1088
7. Banerjee AV (1992) A simple model of herd behavior. Q J Econ 107(3):797–817
8. Bass FM (1969) A new product growth for model consumer durables. Manag Sci 15(5):215–227
9. Bass FM, Krishnan TV, Jain DC (1994) Why the Bass model fits without decision variables. Mark Sci 13(3):203–223
10. Bollinger B, Gillingham K (2012) Peer effects in the diffusion of solar photovoltaic panels. Mark Sci 31(6):900–912
11. Brown JJ, Reingen PH (1987) Social ties and word-of-mouth referral behavior. J Consum Res 14(3):350–362
12. Brunnermeier MK (2001) Asset pricing under asymmetric information: bubbles, crashes, technical analysis, and herding. Press on Demand, Oxford University
13. Cai H, Chen Y, Fang H (2009) Observational learning: evidence from a randomized natural field experiment. Am Econ Rev 99(3): 864–882
14. Chen Y, Wang Q, Xie J (2011) Online social interactions: a natural experiment on word of mouth versus observational learning. J Mark Res 48(2):238–254
15. Chen Y, Xie J (2008) Online consumer review: word-of-mouth as a new element of marketing communication mix. Manag Sci 54(3): 477–491
16. Chevalier JA, Mayzlin D (2006) The effect of word of mouth on sales: online book reviews. J Mark Res 43(3):345–354
17. Cipriani M, Guarino A (2005) Herd behavior in a laboratory financial market. Am Econ Rev 95(5):1427–1443
18. Deutsch M, Gerard HB (1955) A study of normative and informational social influences upon individual judgment. J Abnorm Soc Psychol 51(3):629–636
19. Devenow A, Welch I (1996) Rational herding in financial economics. Eur Econ Rev 40(3–5):603–615
20. Ding AW, Li S (2019) Herding in the consumption and purchase of digital goods and moderators of the herding bias. J Acad Mark Sci 47(3):460–478
21. Ding M, Eliashberg J, Huber J, Saini R (2005) Emotional bidders—an analytical and experimental examination of consumers' behavior in a priceline-like reverse auction. Manag Sci 51(3):352–364
22. Duan W, Gu B, Whinston AB (2008) Do online reviews matter?—an empirical investigation of panel data. Decis Support Syst 45(4): 1007–1016
23. Falk A, Ichino A (2006) Clean evidence on peer effects. J Labor Econ 24(1):39–57
24. Gigerenzer G, Todd PM, the ABC Research Group (1999) Simple heuristics that make us smart. Oxford University Press, New York, NY
25. Hawkins SA, Hoch SJ (1992) Low-involvement learning: memory without evaluation. J Consum Res 19(2):212–225
26. Herzenstein M, Dholakia UM, Andrews RL (2011) Strategic herding behavior in peer-to-peer loan auctions. J Interact Mark 25(1):27–36
27. Hong H, Kubik JD, Solomon A (2000) Security analysts' career concerns and herding of earnings forecasts. RAND J Econ 31(1): 121–144
28. Hu Y, Li X (2011) Context-dependent product evaluations: an empirical analysis of internet book reviews. J Interact Mark 25(3):123–133
29. Kahneman D (2011) Thinking, Fast and Slow. Farrar, Straus and Giroux, New York, NY
30. Lal R, Sarvary M (1999) When and how is the internet likely to decrease price competition? Mark Sci 18(4):485–503
31. Lamont OA (2002) Macroeconomic forecasts and microeconomic forecasters. J Econ Behav Organ 48(3):265–280
32. Lu S, Xiao L, Ding M (2016) A video-based automated recommender (VAR) system for garments. Mark Sci 35(3):484–510
33. Nickell S (1981) Biases in dynamic models with fixed effects. Econometrica 49(6):1417–1426
34. Raafat RM, Chater N, Frith C (2009) Herding in Humans. Trends Cogn Sci 13(10):420–428
35. Sacerdote B (2001) Peer effects with random assignment: results for Dartmouth roommates. Q J Econ 116(2):681–704
36. Shiller RJ (1995) Conversation, information, and herd behavior. Am Econ Rev 85(2):181–185
37. Sias RW (2004) Institutional herding. Rev Financ Stud 17(1):165–206
38. Simonsohn U, Ariely D (2008) When rational sellers face nonrational buyers: evidence from herding on Ebay. Manag Sci 54(9): 1624–1637
39. Tirunillai S, Tellis GJ (2012) Does chatter really matter? Dynamics of user-generated content and stock performance. Mark Sci 31(2): 198–215
40. Trueman B (1994) Analyst forecasts and herding behavior. Rev Financ Stud 7(1):97–124
41. Tucker C, Zhang J (2011) How does popularity information affect choices? A field experiment. Manag Sci 57(5):828–842
42. Wang LC, Baker J, Wagner JA, Wakefield K (2007) Can a retail web site be social? J Mark 71(3):143–157
43. Wang X, Hu Y (2009) The effect of experience on internet auction bidding dynamics. Mark Lett 20(3):245–261
44. Welch I (2000) Herding among security analysts. J Financ Econ 58(3):369–396
45. Wilson S (2008) "Big Break," *Entrepreneur*, (accessed September 13, 2019), [available at https://www.entrepreneur.com/article/192754]
46. Zaichkowsky JL (1985) Measuring the involvement construct. J Consum Res 12(3):341–352
47. Zhang J, Liu P (2012) Rational herding in microloan markets. Manag Sci 58(5):892–912
48. Zhang X, Li S, Burke RR, Leykin A (2014) An examination of social influence on shopper behavior using video tracking data. J Mark 78(5):24–41
49. Zhu F, Zhang X (2010) Impact of online consumer reviews on sales: the moderating role of product and consumer characteristics. J Mark 74(2):133–148