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History Matters: The Impact of Online Customer Reviews Across Product Generations

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Abstract. We examine how online customer reviews for one generation of a product affect sales of another generation in the same product series. The main intriguing result is that previous generation valence has a positive impact on current generation sales; however, current generation valence has a negative impact on previous generation sales. The positive impact of previous generation valence becomes even stronger (1) as the uncertainty (standard deviation) in reviews for the current generation increases and (2) when the current generation valence is high. In contrast, it becomes weaker (1) as the uncertainty in reviews for the previous generation increases and (2) when the current generation has been on the market for a longer period of time. Other results are discussed. Our data consist of intergenerational pairs of point-and-shoot cameras on the largest online seller of such devices, Amazon.com. We estimate the current and previous generation models jointly, allowing for errors to be clustered at the daily and product levels. In addition, we address endogeneity concerns over the online word of mouth measures by using instrumental variables.

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Introduction

When consumers search for online customer reviews of a given product, they often encounter reviews for previous generations in the same product series. In many cases, the previous generation is still available for purchase in the new product market, making these reviews a source of information about both the current generation and an alternative choice in the form of the previous generation (Stokey 1981, Bond and Samuelson 1984, Gul et al. 1986, Kahn 1986, Ausubel and Deneckere 1989, Ramachandran and Krishnan 2008, Krishnan and Ramachandran 2011, Gopal et al. 2013, Borkovsky 2017). For example, consumers in the market for an entry-level digital single-lens reflex (DSLR) camera will find reviews for Nikon's current D3500, as well as the previous generation D3400, both of which can be purchased new from brick-and-mortar and online retailers.

There are several reasons why consumers might turn to and be influenced by reviews for a previous generation of a product as they shop the current generation. First, products in a series usually exhibit substantial similarity to one another (Ellison and Fudenberg 2000, Ramachandran and Krishnan 2008, Borkovsky 2017). Therefore, reviews of older generations provide a degree of information about the current generation because many aspects of the previous generation carry over to the new generation (Borkovsky 2017). Second, the presence of the older generation in the market naturally brings it into the consideration set of consumers, leading to its evaluation alongside the current generation, including an assessment of its reviews. As we show later, it takes very little effort for the average consumer to identify and examine reviews for the previous generation. Finally, when consumers feel they cannot get enough information from the reviews of the current generation because of the lack of a clear consensus or because it has not been on the market very long, they are likely to examine reviews for the previous generation to help resolve this uncertainty.

In this research, we investigate whether, how, and when intergenerational online customer reviews affect product sales. Despite the importance of intergenerational reviews, there has been no systematic investigation of their role in the online purchase environment. This issue is especially important given the dual role that reviews for one generation play in influencing the purchase of another. On one hand, reviews of one generation provide information that is likely to apply to the other generation. To the extent that this information is positive, these reviews may promote sales of the other generation (complementary effect). On the other hand, positive reviews for one generation may encourage consumers to purchase that generation instead of the other generation (substitution effect).

What makes the complementarity or substitution associated with intergenerational reviews particularly interesting is that the effects need not be the same in both directions. The naïve prediction would be that these effects are symmetrical, meaning that if, for example, positive reviews for the previous generation help sales of the current generation, then positive reviews for the current generation should help sales of the previous generation. However, the temporal ordering of the two generations creates a situation in which an asymmetry might exist. In particular, if consumers hold a (potentially biased) expectation of product improvement over time (Kunda 1990, Frey et al. 2013), this could affect their perception of the degree to which reviews for one generation provide accurate information about the characteristics and performance of the other. Under this mindset, consumers may view positive aspects of the previous generation as likely to remain or be improved upon in the current generation, whereas positive aspects of the current generation might not have been present in the previous generation. Hence, positive aspects of the previous generation would be assumed to carry over to the current generation, creating complementarity between previous generation valence and current generation sales. In contrast, positive aspects of the current generation would not necessarily carry back to the previous generation. Therefore, review sentiment for the current generation may cause substitution and lower sales for the previous generation because some of these positive aspects might only be available in the newer generation.

In addition to the questions of whether and how intergenerational reviews affect product sales, a second major issue we investigate is when the carryover from previous generation reviews to current generation sales—which is at the heart of the dynamic impact of reviews from one generation to another—will be the strongest or the weakest. Drawing on economic theories of uncertainty and risk (Kreps 1988, Hardie et al. 1993, Mas-Colell et al. 1995, Novemsky and Kahneman 2005, Kahneman and Tversky 2013), we anticipate that this carryover will be stronger (1) when there is more uncertainty (standard deviation) in the reviews of the current generation and (2) when the current generation valence is high. The first condition suggests that consumers will turn to additional sources of information, including reviews for the previous generation. The second makes it more likely for the product to advance deeper into the consideration process, at which point consumers engage in more elaborate processing (Cox 1967, Murray 1991, Smith and Bristor 1994), and reviews for the previous generation are more likely to enter into the evaluation process. Said differently, poorly rated current generations may not remain under consideration long enough to be influenced as much by previous generation reviews. In contrast, we expect the impact of previous generation valence to diminish (1) when there is a high degree of uncertainty (standard deviation) in the reviews of the previous generation and (2) as the duration for which the current generation has been available on the market increases. When there is a high degree of uncertainty in the reviews of the previous generation, consumers are less likely to put a lot of emphasis on their valence, given the lack of agreement among reviewers. Likewise, when the current generation has been available for a long period of time, consumers have a larger number of sources from which they can obtain information about the product, making prior generation reviews less essential.

The final issue we examine concerns two key moderators of previous generation sales. First, we expect the substitution effect of current generation reviews on previous generation sales to increase as the release gap between the product generations increases. A larger release gap suggests a greater improvement in the current generation, making the previous generation less attractive and enhancing the strength of the substitution effect away from the previous generation, should the current generation receive good reviews. Second, when the current generation valence is high, we also expect the substitution effect to be stronger, which will tend to weaken the influence of previous generation reviews. Using review, sales rank, and pricing data for 67 intergenerational pairs of point-and-shoot cameras on the largest online seller of such devices, Amazon.com, we find support for these hypothesized relationships.

The results have important implications for the literature on online word of mouth. Although this literature has resulted in a deep understanding of how reviews influence sales, who writes reviews, and why, it has yet to consider the influence of reviews for one product generation on the sales of another. With companies allocating larger portions of their marketing budgets to generate and manage the online word of mouth process (Moorman 2014) and with many products belonging to generational product series, only focusing on reviews for the focal generation is likely to result in an incomplete picture of the importance of online reviews. Indeed, one of the principal conclusions from our study is just how large a role previous generation reviews play in determining sales of the current generation.

The remainder of this paper is organized as follows. First, we review the relevant literature on online word of mouth and product generations, highlighting our research contributions. We then describe the data, models, and results. This is followed by a discussion of theoretical and managerial implications. We conclude with limitations and suggestions for future research.

Related Literature

Online Word of Mouth

Online word of mouth is an important source of information that consumers consider when making purchase decisions (Cheung and Lee 2012, Kumar and Pansari 2016). Most existing studies of review influence use a volume and valence approach in which reviews are decomposed into the total volume of reviews and their average rating or valence (Dellarocas and Narayan 2006, Floyd et al. 2014, Tang et al. 2014, Tirunillai and Tellis 2014, Wu et al. 2015). A subset of existing studies also considers the variance or standard deviation in ratings across reviews (e.g., Godes and Mayzlin 2004, Clemons et al. 2006, Moe and Trusov 2011, Sun 2012). The majority of extant studies report a positive relationship between review valence and sales. Examples include Chevalier and Mayzlin (2006), Dellarocas et al. (2007), Chen and Xie (2008), and Li and Hitt (2008). Many studies also find a positive effect of review volume on sales (e.g., Zhu and Zhang 2010, Moe and Trusov 2011). Existing empirical evidence on the variance of reviews is mixed. Studies find that it helps (Moe and Trusov 2011, Sun 2012), hurts (Zhu and Zhang 2010), or has no effect on sales (Zhang 2006). Most studies also find that the impact of reviews decreases over time (Godes and Mayzlin 2004; Moul 2007; Duan et al. 2008a, b; Hu et al. 2008).

A number of studies in the literature expand on the volume-valence-standard deviation focus. For example, Kumar and Benbasat (2006) demonstrate that merely allowing recommendations and reviews improves the perceived usefulness of a website in a laboratory experiment using real-time data from Amazon.com. Forman et al. (2008) find that compared with anonymous reviews, reviews from people who choose to reveal their identity (name, location) are more effective. Trusov et al. (2009) compare traditional marketing versus word of mouth from social media and find that the impact of traditional marketing decays in a few days, whereas the impact of word of mouth from social media persists for approximately three weeks. Villanueva et al. (2009) similarly compare customers acquired through traditional marketing with those gained via word of mouth. They demonstrate that customers from traditional marketing contribute more in the short term but that customers acquired through word of mouth contribute more in the long term.

Many studies have also focused on what drives online ratings and the influence of prior ratings on subsequent ratings. Customers have to first make a purchase decision and then make a decision about whether to write a review, with potential self-selection in both stages (Li and Hitt 2008, Hu et al. 2009, Moon et al. 2010, Moe and Schweidel 2012). Wu and Huberman (2008) report that customers are more likely to post a review when the expected impact is high. Li and Hitt (2008) find that later reviewers tend to give lower ratings because they are different from customers who buy early. Godes and Silva (2012) find that as more ratings amass for a product, the increase in reviewers' dissimilarity leads to lower valence. Wu and Huberman (2008) reveal that subsequent reviewers are likely to follow the trend created by early reviewers, and this opinion becomes more extreme over time. Moe and Trusov (2011) find that existing positive reviews encourage negative reviews, whereas disagreement in existing reviews discourages extreme reviews. Moe and Schweidel (2012) show that frequent reviewers differentiate themselves by posting negative reviews, whereas infrequent reviewers tend to follow the trend.

Although the positive effect of review valence is a principal expectation in the literature, a surprising number of studies have failed to find such a relationship. Chen et al. (2004) report no effect of valence on sales in a data set collected from Amazon.com. Liu (2006) finds that valence does not affect sales, whereas volume does. Duan et al. (2008a) also find that review valence has no impact on the adoption of software. Duan et al. (2008b) similarly find that the valence of online ratings is not persuasive in the context of motion pictures, although the volume of reviews increases awareness. Chintagunta et al. (2010), however, argue that it is indeed the valence of reviews, not volume, that affects the movie box office after accounting for prerelease advertising. We use an approach similar to prior research by focusing on the volume, valence, and standard deviation of current and previous generation reviews.

Product Generations

The relationships between different generations of a product have drawn a considerable degree of attention in the marketing, new product development, and economics literatures. Most of this attention has focused on the detrimental effect of the anticipated launch of future generations on current generation sales. The earliest work in this area was advanced by Coase (1972). He argued that, even for monopolists, it is difficult to protect sales of the current generation from the negative influence of expectations for a new generation. Various researchers have reported that this conjecture holds in certain conditions (Stokey 1981, Gul et al. 1986, Ausubel and Deneckere 1989) but does not hold in others, such as when the durable good depreciates (Bond and Samuelson 1984), when costs increase (Kahn 1986), or when buyers face future competition (Fuchs and Skrzypacz 2010). Aligned with Coase's conjecture, many studies have reported that introducing a newer version of a product can directly or indirectly affect sales of the previous generation, mostly because the introduction of the new version affects the perceived value of the previous generation (Levinthal and Purohit 1989, Waldman 1993, Choi 1994, Dhebar 1994, Ellison and Fudenberg 2000).

Many solutions have been proposed to address the problem of two generations competing with one another, including easing the pace of innovation (Dhebar 1996), buybacks (Fudenberg and Tirole 1998), pricing tactics (Kornish 2001), free new version rights for software (Sankaranarayanan 2007), and modular upgradability (Ramachandran and Krishnan 2008). Besanko and Winston (1990) show that price skimming is optimal when consumers are rational. Padmanabhan and Bass (1993) suggest that the optimal pricing strategy depends on the degree of substitutability across the two generations and that crossgenerational effects have important implications for a firm's optimal pricing strategy. Danaher et al. (2001) also reported price response interactions between generations. The key takeaway from these studies for our purposes is that it is important to model both generations when considering products belonging to a generational series.

Despite the depth and breadth of research into the effect of one product generation on another, we know of no study investigating the impact of product *reviews* for one generation on the sales of another. Whereas the presence of an older generation or the introduction of a newer generation would seem very likely to dampen sales of the other, the same cannot be said for reviews because positive word of mouth for generational series can build over time, thereby supporting newer generations. Similarly, well-received newer generations can conceivably support the sales of older generations offered at typically lower prices.

Research Contributions

In this research, we study the impact of product reviews for one generation on the sales of another. Specifically, we pose the following two research questions. (1) Do intergenerational reviews matter, and are they complements or substitutes? (2) What factors alter the carryover from reviews of one generation to sales of the other? Our research contributes to the online word of mouth literature by providing the following insights.

1. *Reviews of other product generations matter*. For products belonging to a generational series, reviews of both generations matter. For current generation sales in particular, the elasticity of review valence is significantly larger when considering the reviews of both generations. The strong carryover from previous generation reviews to current generation sales is expected because (1) the most important differences between the series of one brand versus another will often feature more prominently in early generation reviews and (2) there are usually more reviews for the previous generation than for the current generation. Although it is not surprising that reviews for another product, in general, would matter, the effects of reviews for other products are usually small and included in studies mainly as control variables if at all. As we demonstrate in this paper, the product's immediate predecessor or successor is an exception and has a very significant influence on sales of the product.

2. *Reviews of other product generations can complement sales*. Different generations in a product series compete with each other, so their reviews can cause the substitution of one generation for another. However, reviews for other generations also help the series compete against the offerings of other brands. Hence, positive reviews for another generation can increase brand incidence. This complementary effect dominates substitution in shaping the influence of previous generation reviews on current generation sales. Unlike all other products, the previous generation serves as both a competitor to the current generation and evidence of the quality of the series as it competes against other brands. We show that when evaluating the current generation, the complementary effect is dominant, and good reviews for the previous generation help sales of the current generation.

3. *Reversing this order reverses the effect*. Although belonging to the same series, reviews of the current generation affect sales of the previous generation in the opposite way, and substitution dominates. Because customers are likely to have the notion that they should "always buy new," especially for electronic products, they may hold priors that support the perceived superiority of the current generation. One consequence of such an orientation is that positive aspects of the previous generation would be assumed to carry over to the current generation as a baseline for performance, whereas positive aspects of the current generation may not have been present in the previous generation.

4. *Uncertainty moderates the impact of intergenerational reviews*. We show that a high standard deviation in reviews for the current generation leads to a higher carryover in the influence of reviews for the previous generation. When reviews of the current generation are contradictory, customers may gather more information from other sources as a way to resolve this uncertainty. One of the most relevant and accessible sources of information is the body of reviews for the previous generation. Customers appear to pay more attention to them or trust them more when reviews of the current generation exhibit less of a consensus in opinion. However, uncertainty in the reviews for the previous generation has the opposite effect. Thus, the complementary effect of previous generation valence on current generation sales diminishes when there is a greater standard deviation in the previous generation ratings.

5. *Rating valence across generations moderates the impact of intergenerational reviews*. We also show that sales of the current generation are impacted to a greater extent by previous generation reviews when the current

generation has a higher valence in its reviews. One consequence of a higher valence is that the current generation is likely to remain in consumers' consideration sets further into the decision-making process. Prior research suggests that products advancing to later stages of consideration receive more extensive and elaborate information processing. The observed effect is consistent with such an expanded role for previous generation reviews.

6. *Timing of release matters*. Finally, we show that previous generation reviews affect current generation products less when the current product has been available on the market for a longer period of time. The longer the product is on the market, the more sources of information become available, which appears to diminish the role of previous generation reviews. In contrast, the negative impact of current generation valence on previous generation sales increases as the release gap between the two generations increases. The most likely explanation is that consumers associate a greater release gap with larger improvements in the current generation, thereby strengthening the substitution effect if the current generation is well reviewed.

Data Description

Our data were collected daily from Amazon.com, the leading online seller of digital point-and-shoot cameras. We generated a list of the top 100 best-selling digital point-and-shoot cameras in late February 2015. We then identified whether each of these 100 products belonged to a product pair or not. Most of them did, and we included these products in our sample along with the previous generation of each product (or the next generation in the rare case that the product in the top 100 was not the latest generation). There were some product pairs where both the current and the previous generation were in the top 100 list, in which case the two products resulted in only a single pair. There were also a number of stand-alone products on the list that were not part of a product series. Because these products had no previous or next generation, they were excluded from the analysis. Finally, one product was dropped by Amazon.com during the data collection period. In the end, we had 67 product pairs (134 individual products) on our final list. We then collected price, sales rank, and review data every day at the same time for these product pairs from March 2015 to August 2015. The final data set for analysis has 8,374 observations and 74,874 reviews. Variable descriptions and summary statistics are shown in Table 1. Online Appendix A shows the list of camera series used in our analysis.

CURRENT (*PREVIOUS*) stands for the current (previous) generation product. Sales rank (*SALES RANK*) is the item's sales rank in the camera category. As in other studies using Amazon.com data, we use sales rank data rather than actual sales. Previous research has shown that there is an approximately linear negative relationship between log sales and log sales rank in a variety of product categories including books, software, yogurt, women's clothing, and electronic products (Goolsbee and Chevalier 2002; Brynjolfsson et al. 2003; Ghose and Sundararajan 2006; Ho-Dac et al. 2013). For example, Brynjolfsson et al. (2003) provide a scaling coefficient of negative 0.871 between log sales and log sales rank on Amazon.com. This approximately linear relationship will hold as long as product sales follow an approximate Pareto distribution (i.e., the 80/20 rule). Hence, log sales rank can be used as a valid linear proxy for log sales (Sun 2012).

Price (*PRICE*) is the list price on Amazon.com. The vast majority of the time, the list price is for products sold by Amazon.com and is the best price. As Amazon.com is an authorized reseller, products sold by Amazon.com are covered by a manufacturer warranty. In very rare cases where Amazon.com was temporarily out of stock, the list price is normally from another authorized reseller, with the same price set by the manufacturer.

Similar to prior studies in this area (e.g., Godes and Mayzlin 2004, Sun 2012), we have the following measures of online word of mouth for the current and previous generation products. *VOLUME* is the number of cumulative reviews for the product, *VALENCE* captures the average rating of these reviews, and *STDEV* is the standard deviation of the reviewer ratings.

There are several measures we use to reflect the impact of competition among the products in the data set. *COMPETITION_VALENCE_OWN* is the average valence of competing products of the same brand, whereas *COMPETITION_VALENCE_OTHER* is the average valence of competing products of other brands. The inclusion of the own-brand variable allows us to examine how previous/current reviews for the product series differ from reviews for other products from the same brand. We also include the variable *NEW_PRODUCTS*, which indicates the number of new products released in the previous month in the camera category as a whole.

Finally, we include the time because release for each product generation (*AVAILABLE*) and the release gap between the two generations (*RELEASE_GAP*). We also control for the extent of precipitation (*WEATHER*). In addition, we have dummy variables for the day of the week and the month to control for seasonality.

Definition of Product Generations

We define a product series based on the existence of a product with routine/incremental upgrades from the previous generation. The new generation is in the

Table 1. Descriptive Statistics

Variable	Description	Mean	Standard deviation	Min	Max
CURRENT SALES RANK$_{it}$	Sales rank of the current generation product *i* at time *t*	863.66	1,925.60	9	29,481
PREVIOUS SALES RANK$_{it}$	Sales rank of the previous generation product *i* at time *t*	2,495.31	2,624.13	8	14,240
VALENCE_CURRENT$_{it}$	Average valence of cumulative reviews for current generation product *i* at time *t*	4.18	0.30	1	5
VALENCE_PREVIOUS$_{it}$	Average valence of cumulative reviews for previous generation product *i* at time *t*	4.19	0.26	3.32	4.77
STDEV_CURRENT$_{it}$	Standard deviation of cumulative reviews for current generation product *i* at time *t*	1.20	0.22	0	2.12
STDEV_PREVIOUS$_{it}$	Standard deviation of cumulative reviews for previous generation product *i* at time *t*	1.19	0.20	0.44	1.73
VOLUME_CURRENT$_{it}$	Cumulative volume of reviews for current generation product *i* at time *t*	324.38	303.90	1	1,397
VOLUME_PREVIOUS$_{it}$	Cumulative volume of reviews for previous generation product *i* at time *t*	466.99	269.01	8	1,414
PRICE_CURRENT$_{it}$	Price of the current generation product *i* at time *t*	256.36	163.91	64.16	797.99
PRICE_PREVIOUS$_{it}$	Price of the previous generation product *i* at time *t*	283.62	234.78	59	1,598
COMPETITION_VALENCE_OWN$_{it}$	Average cumulative valence of own brand competing products for product *i* at time *t*	4.13	0.24	1	5
COMPETITION_VALENCE_OTHER$_{it}$	Average cumulative valence of other brands competing products for product *i* at time *t*	4.18	0.11	2.91	4.38
NEW_PRODUCTS$_{it}$	Number of new products released in the previous month at time *t*	10.36	8.49	2	22
AVAILABLE_CURRENT$_{it}$	Time (days) since release for current generation product *i* at time *t*	491.23	236.29	29	1,274
AVAILABLE_PREVIOUS$_{it}$	Time (days) since release for previous generation product *i* at time *t*	859.06	288.50	394	2,358
RELEASE_GAP$_{it}$	Release gap (days) between focal product *i* and other generation product at time *t*	361.83	132.11	109	1,084
WEATHER$_{it}$	Precipitation at time *t* for product i	1.7508	1.8724	0	7.6001
MON	1 for Monday, 0 otherwise	0.137	0.345	0	1
TUE	1 for Tuesday, 0 otherwise	0.144	0.352	0	1
WED	1 for Wednesday, 0 otherwise	0.144	0.352	0	1
FRI	1 for Friday, 0 otherwise	0.144	0.352	0	1
SAT	1 for Saturday, 0 otherwise	0.144	0.352	0	1
SUN	1 for Sunday, 0 otherwise	0.144	0.352	0	1
INSTRUMENT for VALENCE_CURRENT	Average cumulative rating each reviewer has posted for products in categories other than cameras for the current generation product	4.2373	0.1345	3.7422	4.8001

Table 1. (Continued)

Variable	Description	Mean	Standard deviation	Min	Max
INSTRUMENT for STDEV_CURRENT	Standard deviation of the cumulative ratings each reviewer has posted for products in categories other than cameras for the current generation product	0.5168	0.0656	0.1438	0.7038
INSTRUMENT for VOLUME_CURRENT	Precipitation during the time period during which the reviews were generated for the current generation product	26.9827	1.5066	20.2485	30.5695
INSTRUMENT for VALENCE_PREVIOUS	Average cumulative rating each reviewer has posted for products in categories other than cameras for the previous generation product	4.1830	0.0898	3.9437	4.4825
INSTRUMENT for STDEV_PREVIOUS	Standard deviation of the cumulative ratings each reviewer has posted for products in categories other than cameras for the previous generation product	0.5264	0.0345	0.4566	0.6684
INSTRUMENT for VOLUME_PREVIOUS	Precipitation during the time period during which the reviews were generated for the previous generation product	27.3563	0.5704	25.7456	28.7843
Number of observations		8,374			

same or a very similar market position, and the new generation is released by the manufacturer to ultimately replace the old generation. This differs from a product line, which consists of different products with different market positions but with some common features. A product line targets different customer segments, whereas a product series involves technological upgrades and/or fixes to the problems of the previous generation.

In this research, we operationalize product generations as product pairs belonging to the same series. The two generations of the same series usually look virtually identical or very close to each other. Weight and portability are significant differences in cameras, and a manufacturer will seldom change these aspects for the same series. Sometimes, manufacturers will use the same mold to produce the casing, resulting in the same appearance in both generations. The upgrades within a series are typically about upgrading lenses, adding features such as Wi-Fi, and so on. We identify the current and previous generations of the same series primarily from the model number, the manufacturer's official website, professional critics websites, and Amazon.com.

The model number in particular provides substantial information about the series. For example, the Canon SX530 and SX540 are a product generation pair. However, neither the Canon SX430 nor the SX730 would be the appropriate previous generation product for the Canon SX540. SX stands for super zoom, which is the focus of the SX product line. However, beyond just super zoom, there are series within the SX product line. The SX4 series, as the entry-level offering, does not have the HS (high-sensitivity) system. Although both the SX5 series and the SX7 series have the HS system, the SX5 and SX7 series cameras differ greatly by shape. The SX7 series is much smaller in size and is the higher-end model of the SX product line. Common issues for small-size electronics (SX7 series) are cooling and battery life, whereas common issues for larger-size electronics (SX5 series) are weight and portability. Thus, for consumers considering the SX540, the SX530 is a much better source of information because the SX540 is a direct upgrade from the SX530, and both belong to the SX5 series.

The manufacturer's official website is also a major source to identify cameras belonging to a series. The manufacturer's website often provides information about the current and previous generation cameras in a series. It is worth noting that some manufacturers use a looser definition of series. Canon, for instance, has many camera series, including five series that have a model name starting with "G" (G1, G3, G5, G7, and G9). Although Canon calls all these cameras "G series," it is actually the "G product line" as each of the five series has different features and quality levels, has a different price point, and is targeting a different customer segment. We use the actual product series in this research.

Professional critics (e.g., *CNET* and *Digital Photography Review*) also typically compare the current generation camera with the older model in the series. Figure 1 shows examples of these comparisons for some series cameras. All these professional sources allow a customer to identify the previous generation corresponding to the product they are considering. Moreover, Amazon also helps consumers identify current and previous generations in multiple ways. Customer reviews sometimes mention the previous generation product (Figure 2(a)). In addition, the previous generation product page (Figure 2(b)) sometimes adds "OLD MODEL" to the name of the previous generation product and "There is a newer model of this item."

Empirical Analysis

Do Intergenerational Reviews Matter, and Are They Complements or Substitutes?

In general, we would expect the sales of any focal generation to be most influenced by its own reviews and reviews of any other generation to act in the same manner regardless of whether the flow was "forward" from previous reviews to current sales or "backward" from current reviews to previous sales. However, the marketing literature contains many examples in which consumers rely instead on simplifying heuristics because of either limitations in their own decision-making resources or imperfect information in the decision-making environment (Bartlett 1932, Ross 1979, Huber et al. 1982, Huber and Puto 1983, Kurz-Milcke and Gigerenzer 2007, Aronson et al. 2012). Our goal in this section is to suggest that (1) the effect of reviews for a focal generation on its sales may not be substantially greater than the effect of reviews for another generation and (2) that effects can be asymmetrical when going forward versus backward in time.

With respect to the first issue, reviews of the previous generation can inform the decision of whether to purchase the current generation because key features and performance of the previous generation are likely to carry over to the current generation. Moreover, in many instances, the attributes that are most important in determining the relative performance of one series versus that of another brand will emerge in the earlier generations of the series. These critical interbrand differences will be reflected prominently in the reviews for earlier generations, whereas reviews of later generations may focus more on incremental features and comparisons with previous generations within the series. As a result, previous generation reviews may exhibit a positive and larger than expected impact on current generation sales because they contain more information about these important aspects of the series than current generation reviews. In our data, we find that the cumulative volume of previous generation reviews is twice the cumulative volume of current generation reviews on average and that the median review length for the previous generation is also 30% more than for the current generation.

With respect to the second issue, it is possible that an asymmetry in effects will be observed when going from previous reviews to current sales versus current reviews to previous sales. One reason for this is that, as alluded to, consumers may hold potentially biased expectations of product improvement over time (Kunda 1990, Frey et al. 2013). This amounts to an assumption that the features and performance associated with a given generation are not lost over time when moving forward to the next generation. Instead, new features are added, and problematic areas of performance are improved upon. This need not happen in every case, but it is reasonable to expect that consumers have learned to make such an assumption, particularly for technologically oriented products.[1] If features and performance are assumed to be additive in this manner, reviews for older generations provide a degree of information about the current generation because they establish a baseline onto which new features and performance are added. A higher baseline as indicated by a higher review valence for the previous generation implies that the new version is at least as good if not better. Hence, in the forward direction, reviews for the previous generation will tend to be complementary to sales of the current generation. In the backward direction, because positive reviews for the current generation might be because of features that were not present in the previous generation, their complementary effect on sales of the previous generation is limited. Instead, high review valence for the current generation could be taken to suggest a high degree of improvement, which would encourage consumers to substitute the current generation for the previous.

We use log-log fixed effects models throughout the investigation to control for time-invariant unobserved product-specific characteristics. The dependent variables in the models are the natural logs of either the current or previous generation sales rank. We do *not* invert the sales rank variable; hence, negative coefficients indicate higher sales. We add one to the raw score for all variables before taking the natural log. We lag the review variables, such that they represent the cumulative volume, valence, and standard deviation of reviews posted through the day prior to the date sales rank is measured. Using lags of the review variables helps assure that sales are not driving reviews, such as might happen if a consumer posts a review after buying a product but before receiving it.

We specify two models. The first (second) model investigates the forward (backward) effects of intergenerational product reviews on sales. Specifically, the

Figure 1. (Color online) Examples of Product Generation Comparisons

(a)

Digital Photography Review's Comparison Between Samsung's Galaxy Camera 2 and Galaxy Camera (https://www.dpreview.com/reviews/samsung-galaxy-camera-2)

Galaxy Camera vs Galaxy Camera 2 key differences

	Galaxy Camera	Galaxy Camera 2
Sensor	16.3MP BSI-CMOS	
Lens	F2.8-5.9 23-483mm equiv.	
Processor	1.4Ghz quad-core Exynos 4412	1.6GHz quad-core Exynos 4412
RAM	1GB	2GB
Android version	4.1	4.3
Display	4.8" 720p touchscreen LCD (16:9)	
Wi-Fi	802.11a/b/g/n/a (dual band)	
NFC	No	Yes
3G/4G connectivity	Optional	No
Video	1080/30p (MPEG-4)	
Battery capacity	1650 mAh	2000 mAh
Battery life (CIPA)	340 shots	400 shots
Dimensions (WxHxD)	71 x 129 x 19 mm	71 x 133 x 19 mm
Weight	302 g	285 g

(b)

CNET's review of Nikon Coolpix L830 (https://www.cnet.com/reviews/nikon-coolpix-l830-review/)

CNET › Photography › Cameras › Nikon Coolpix L830

The Nikon Coolpix L830 is all about giving you an affordable long-zoom camera that's not bloated with features you might never use, but has just enough of them to keep you from feeling cheated or like you're missing out.

It's a modest update from last year's L820, which was a good deal as well. In fact, the differences between the two pretty much come down to three features: a tilting LCD (the L820's was fixed), a little extra zoom (765mm compared to 675mm), and a Dynamic Fine Zoom that digitally extends the zoom range to 1,530mm.

There are a couple of other minor differences including improved battery life from its four, AA-size batteries, but generally speaking, it's those three things that separate the two. It's well priced for what you're getting: it starts at $299.95 (£229.99, $299 AU), but can be found for considerably less.

Notes. (a) *Digital Photography Review*'s comparison between Samsung's Galaxy Camera 2 and Galaxy Camera (https://www.dpreview.com/reviews/samsung-galaxy-camera-2). (b) *CNET*'s review of Nikon Coolpix L830 (https://www.cnet.com/reviews/nikon-coolpix-l830-review/). (c) *Digital Photography Review*'s review of Canon PowerShot G16 (https://www.dpreview.com/reviews/first-impressions-review-using-the-canon-powershot-g16).

Figure 1. (Continued)

(c)

Digital Photography Review's review of Canon PowerShot G16
(https://www.dpreview.com/reviews/first-impressions-review-using-the-canon-powershot-g16)

When the Canon PowerShot G16 was announced recently there was a general sense of mild anticlimax, both on the part of the journalists assembled at Canon's HQ in Long Island, and among some of our readers here at dpreview.com. To a casual glance the G16 might look like 'just' a G15 with a new processor, tweaked movie settings and Wi-Fi, making it a decidedly *iterative* upgrade.

On the other hand, the G15 was (and still is) a camera that we liked a lot, and has proven itself a solid and reliable performer in all of the conditions in which we've used it. The G15 is fast, turns out good images, and has a decent feature set. It's the kind of camera we recommend to friends.

Canon PowerShot G16 - Key Features

- 12MP CMOS sensor
- 28-140mm (equivalent) F1.8-2.8 zoom
- ISO 80-12800
- Fixed, 3in 622k-dot LCD screen
- DIGIC 6 Processor
- 1080p/60p video mode
- Up to 9.3fps continuous shooting
- Built-in Wi-Fi

The G16 isn't a vastly different product, it's true. But it is a better one. The G16 still offers 12MP and, while Canon USA is saying it's the same conventional CMOS sensor as the G15, Canon Japan says it's a BSI CMOS design, which should mean improved low-light performance. The DIGIC 6 processor delivers what Canon claims is a ~50% increase in speed where it counts - shutter lag and AF acquisition, and the convenience of built-in Wi-Fi has the potential to appeal to a lot of people.

first (second) model investigates how lagged reviews of both the previous generation and the current generation affect sales of the current (previous) generation for product pair i at time t:

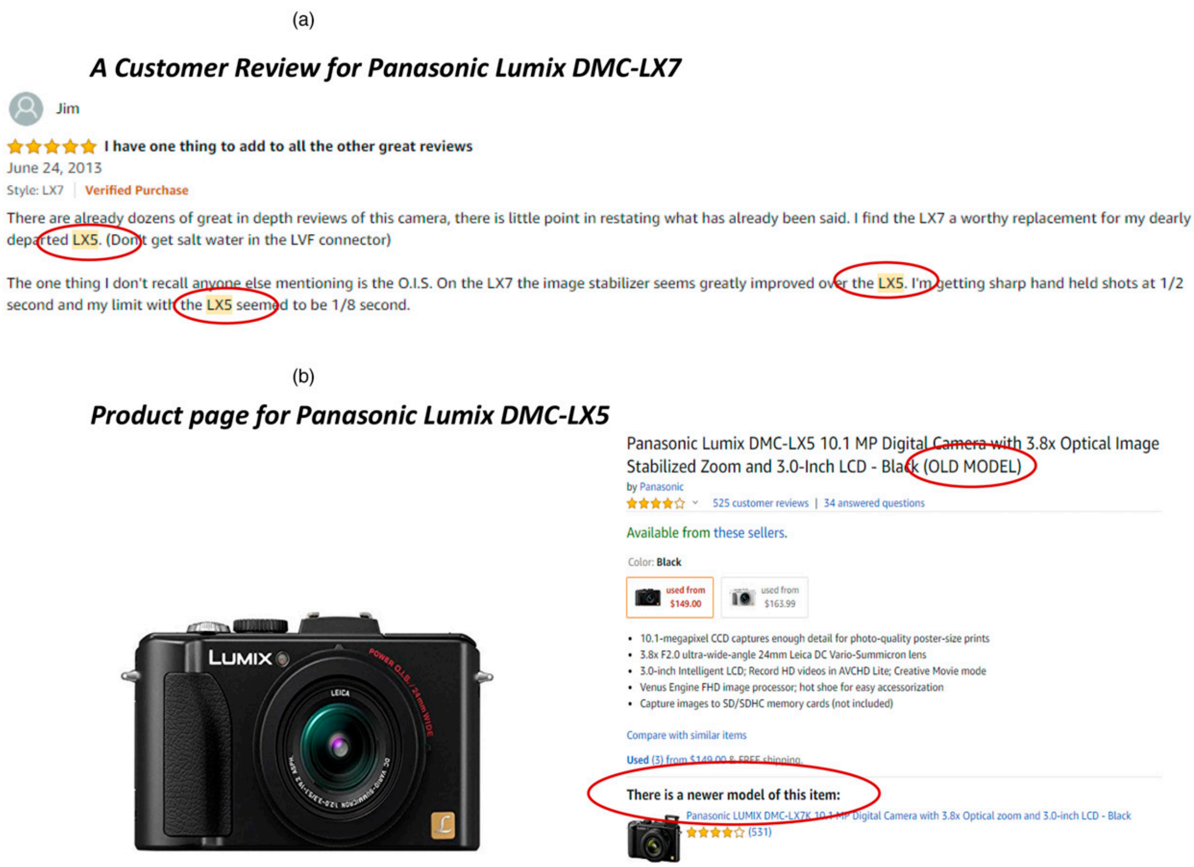
$$\begin{aligned}
&\log(CURRENT\ SALES\ RANK_{it})\\
&\quad= \alpha_i^C + \beta_1^C\log(PRICE_CURRENT_{it-1})\\
&\qquad+ \beta_2^C\log(PRICE_PREVIOUS_{it-1})\\
&\qquad+ \beta_3^C\log(VALENCE_CURRENT_{it-1})\\
&\qquad+ \beta_4^C\log(VALENCE_PREVIOUS_{it-1})\\
&\qquad+ \beta_5^C\log(STDEV_CURRENT_{it-1})\\
&\qquad+ \beta_6^C\log(STDEV_PREVIOUS_{it-1})\\
&\qquad+ \beta_7^C\log(VOLUME_CURRENT_{it-1})\\
&\qquad+ \beta_8^C\log(VOLUME_PREVIOUS_{it-1})\\
&\qquad+ \beta_9^C\log(COMPETITION_VALENCE_OWN_{it-1})\\
&\qquad+ \beta_{10}^C\log(COMPETITION_VALENCE_OTHER_{it-1})\\
&\qquad+ \beta_{11}^C\log(NEW_PRODUCTS_{it-1})\\
&\qquad+ \beta_{12}^C\log(AVAILABLE_CURRENT_{it-1})\\
&\qquad+ \beta_{13}^C\log(AVAILABLE_CURRENT_SQ_{it-1})\\
&\qquad+ \beta_{14}^C\log(WEATHER_{it}) + \Gamma^C(D_{it}) + \Theta^C(M_{it}) + u_{it}^C
\end{aligned} \tag{1}$$

$$\begin{aligned}
&\log(PREVIOUS\ SALES\ RANK_{it})\\
&\quad= \alpha_i^P + \beta_1^P\log(PRICE_CURRENT_{it-1})\\
&\qquad+ \beta_2^P\log(PRICE_PREVIOUS_{it-1})\\
&\qquad+ \beta_3^P\log(VALENCE_CURRENT_{it-1})\\
&\qquad+ \beta_4^P\log(VALENCE_PREVIOUS_{it-1})\\
&\qquad+ \beta_5^P\log(STDEV_CURRENT_{it-1})\\
&\qquad+ \beta_6^P\log(STDEV_PREVIOUS_{it-1})\\
&\qquad+ \beta_7^P\log(VOLUME_CURRENT_{it-1})\\
&\qquad+ \beta_8^P\log(VOLUME_PREVIOUS_{it-1})\\
&\qquad+ \beta_9^P\log(COMPETITION_VALENCE_OWN_{it-1})\\
&\qquad+ \beta_{10}^P\log(COMPETITION_VALENCE_OTHER_{it-1})\\
&\qquad+ \beta_{11}^P\log(NEW_PRODUCTS_{it-1})\\
&\qquad+ \beta_{12}^P\log(AVAILABLE_PREVIOUS_{it-1})\\
&\qquad+ \beta_{13}^P\log(AVAILABLE_PREVIOUS_SQ_{it-1})\\
&\qquad+ \beta_{14}^P\log(WEATHER_{it})\Gamma^P(D_{it}) + \Theta^P(M_{it}) + u_{it}^P,
\end{aligned} \tag{2}$$

where $D_{it} = (SUN_{it}, MON_{it}, TUE_{it}, WED_{it}, THU_{it}, FRI_{it}), M_{it} = (MAR_{it}, APR_{it}, MAY_{it}, JUN_{it}, JUL_{it})$, and *CURRENT* and *PREVIOUS* in the variable names refer to the product generation.

Endogeneity. A key problem in modeling the effects of online word of mouth is the endogeneity of product reviews. Endogeneity occurs when there is correlation

Figure 2. (Color online) How Amazon Aids in Identifying Product Generations



Notes. (a) A customer review for Panasonic Lumix DMC-LX7. (b) Product page for Panasonic Lumix DMC-LX5.

between an explanatory variable and the unobserved factors in the error term of the model. As a result, the conditional expectation of the endogenous variable will not equal to zero. This violates a key assumption for the estimator to be consistent (Greene 2003). In our research context, the main concern is that unobservable product characteristics such as quality, performance, and brand equity will influence both reviews and sales, leading to spurious associations. The use of product fixed effects (α_i) in the models controls for time-invariant sources of endogeneity like these. However, time-varying factors like offline word of mouth and advertising may drive both sales and reviews and are not eliminated by fixed effects.[2] We control for this in part by including day of the week effects (Γ) and month effects (Θ). In addition, we use an identification strategy based on instrumental variables to account for any remaining unobserved time-varying sources of endogeneity. The set of instruments we use is based on prior research (e.g., Chintagunta et al. 2010, Yazdani et al. 2018).

Our instrument for *VOLUME* is the extent of precipitation during the time period when the reviews were generated for the current generation product. The idea is that people are more likely to stay indoors on rainy/snowy days and spend more time writing reviews. The identifying assumption is that, conditional on camera characteristics, etc., covariation between the volume of reviews and the extent of precipitation is because of the supply of time for writing reviews and not because of unobserved demand factors.

The volume instrument is constructed as follows. Recall that volume indicates the number of reviews posted until (but not including) the focal day. Hence, our volume instrument is based on the weather during prior days when the reviews were written but does not include the focal day. For illustration, suppose we are looking at sales on day 30; the volume measure is based on the reviews generated during the first 29 days, and the volume instrument is also based on the weather in these first 29 days. However, it is possible that the weather on the 30th day could affect sales on the 30th day. Hence, we control for this in the model with the variable *WEATHER*. In addition, although Chintagunta et al. (2010) use an instrument based on national-level precipitation data, there is considerable variation in precipitation at the local level. Hence, we account for these local differences in precipitation when creating the instrument. Specifically, we collect daily precipitation data from the National Climatic Data Center (https://www.ncdc.noaa.gov/) for each weather station and aggregate it to the county level. In the United States, there are over 3,100 counties and more than 61,000 weather stations. For example, Bristol County, Massachusetts has 38 weather stations. After we have the county-level daily precipitation data, we weight it by county population data from the U.S. Census Bureau (https://www.census.gov/) and aggregate it to the national level to get the volume instrument.

For *VALENCE*, our instrument is the average cumulative rating each reviewer of the product at time $t-1$ has posted for products in categories other than cameras. The intuition is that such an instrument shows the natural rating tendency of a specific reviewer, which influences his or her rating for the focal camera but does not directly influence the focal camera's sales. One threat to the validity of the instrument would arise if products differed in their appeal to more strict versus more lenient reviewers. Although we cannot completely rule out this possibility, in our analysis we include camera fixed effects, which control for unobserved camera-level time-invariant characteristics. However, it is possible that there still could be lingering time-varying camera characteristics such as improvements in the camera quality over time. Hence, we also include additional controls to alleviate this concern. Specifically, we control for day of the week effects and the age of the camera (i.e., duration) for which the camera has been available for purchase. Our identifying assumption is that, conditional on the various fixed effects, the covariation between the valence of reviews and the instrument can be attributed to factors other than the unobservable characteristics of the camera. Similarly, the instrument for *STDEV* is the standard deviation of the cumulative ratings each reviewer of the product at time $t-1$ has posted for products in categories other than cameras. One would expect the standard deviation in reviewer rating tendencies for other product categories to be positively related to the standard deviation in reviewer ratings for the camera category. The identifying assumption is similar to that for the valence instrument.

The specific steps involved in the creation of these instruments are as follows. First, we identify all the reviewers for product i until time $t-1$. Second, for each of these reviewers, we take the average of their ratings for products in categories other than cameras. This helps us capture the innate rating tendency of the reviewer. Figure 3 shows an example of reviewers with high and low rating tendencies. From the figure, we can see that Reviewer A, on average, has a tendency to give a higher rating than Reviewer B, as indicated by the red lines. After we have the average rating tendency of all the prior reviewers for a product, the instruments are calculated in this manner. The instrument for valence is the average of the rating averages of all prior reviewers for the product. Similarly, the instrument for standard deviation is the standard deviation of the rating averages of all prior reviewers for the product. Descriptive statistics for the instruments for both the current and previous generation products are at the bottom of Table 1.

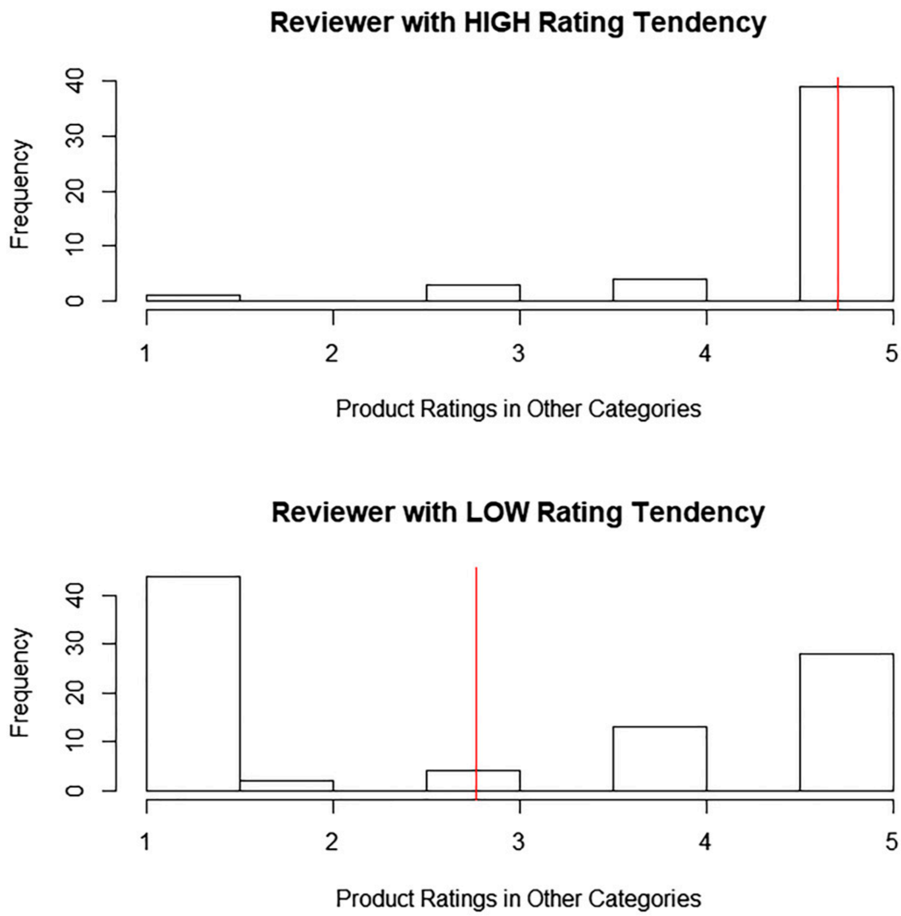
Similar to prior research in this area (e.g., Forman et al. 2008), we treat price as exogenous. This choice is justified in part by the limited within-product variation in price observed in the data.[3]

Results. In Tables 2 and 3, we present results from the regression of the endogenous variables on the instruments, other exogenous variables, and fixed effects. Overall, the first-stage results indicate that the instruments have a significant impact on the corresponding endogenous variables with the expected signs. Specifically, greater precipitation is associated with a greater volume of reviews, a higher rating tendency of prior reviewers is associated with a higher rating valence, and a greater standard deviation in the rating tendency of prior reviewers is associated with a higher rating standard deviation. Moreover, an F test of whether the instruments jointly explain the endogenous variables indicates that the instruments cannot be jointly excluded from the first-stage regressions (all the p-values were less than 0.001). In addition, all the F statistics exceeded the rule of thumb of 10 suggested by Stock and Watson (2015). These results give us some assurance that the proposed instruments are not weak and that we have a reasonable set for our analysis.

We estimate the current generation and previous generation models simultaneously with errors clustered at the daily and product levels. Results appear in Tables 4 and 5. Beginning with Table 4, previous generation valence has a large positive impact on current generation sales, indicating a *complementary* effect. Thus, there is substantial positive carryover from previous generation reviews to current generation sales. Moreover, we see that the coefficient of *STDEV* is also higher for previous generation reviews than for current generation reviews. This suggests that, overall, previous generation reviews play a substantial role in explaining current generation sales.

Table 4 also shows the impact of competition. The valence of competing products of other brands (*COMPETITION_VALENCE_OTHER*) has a negative impact on current generation product sales, as expected. Interestingly, the valence of competing products of the same brand (*COMPETITION_VALENCE_OWN*) also has a significant negative impact. This suggests that although the valence of the previous generation within the series helps the sales of the current generation, the valence of other products of the same brand does not. Finally, we

Figure 3. (Color online) Examples of High and Low Reviewer Rating Tendency



Note. The vertical lines indicate the average of the reviewer's product ratings in other categories.

see an inverted-U shaped relationship for the time the product has been available on the market because it takes time for a product to catch on and then, it is replaced.

The results in Table 5 show that "generation flow" matters. Current generation valence has a negative impact on previous generation sales, indicating a *substitution* effect. In addition, based on the coefficient sizes, current generation reviews seem to be playing a more limited role compared with previous generation reviews. Turning to the other key variables, we find that the valence of competing own-brand products decreases previous generation sales. However, both the valence of other brand products and an increase in the number of new products released increase previous generation sales. We attribute this to category expansion and more exposure to previous generation products through increased traffic. Not surprisingly, previous generation products that have been available on the market for a short time (and for which the current generation is already available, given the nature of our data) sell poorly, whereas previous generations that are kept on the market for a long time sell better.

What Factors Alter the Carryover from Previous (Current) Generation Reviews to Current (Previous) Generation Sales?

We expect the complementarity between previous generation reviews and current generation sales to be moderated under certain key conditions. The first is when consumers confront a high degree of *uncertainty in current generation reviews* as indicated by a high standard deviation in current generation review valence. When this uncertainty is low, the consensus of reviewers is readily apparent, and consumers are likely to cut off their information search sooner. In contrast, when this uncertainty is high, consumers are likely to expand their information search in an effort to resolve uncertainty by consulting additional sources of information. Hence, as the lack of consensus among reviews for the current generation increases, reviews for the previous generation should exhibit a stronger effect on current generation sales. Second, when the *current generation valence* is high, it becomes more likely for the product to enter a consumer's consideration set and remain under consideration longer, at which point consumers may again engage in more elaborate information search and

Table 2. First-Stage Estimates for Endogenous Variables (Current Generation)

	Endogenous variables		
	VALENCE_CURRENT[a]	*STDEV_CURRENT*[a]	*VOLUME_CURRENT*[a]
INSTRUMENT for VALENCE_CURRENT	0.3872*** (0.0208)	−0.1245** (0.0535)	0.1010 (0.1708)
INSTRUMENT for STDEV_CURRENT	−0.0991*** (0.0023)	0.2058*** (0.0060)	0.5635*** (0.0194)
INSTRUMENT for VOLUME_CURRENT	−0.0548*** (0.0055)	0.0260* (0.0141)	0.5697*** (0.0452)
INSTRUMENT for VALENCE_PREVIOUS	−0.2091*** (0.0636)	−2.2694*** (0.1632)	8.297*** (0.5215)
INSTRUMENT for STDEV_PREVIOUS	0.0828*** (0.0318)	−0.8400*** (0.0816)	−0.0214 (0.2609)
INSTRUMENT for VOLUME_PREVIOUS	0.0465*** (0.0060)	−0.0081 (0.0154)	−0.5346*** (0.0492)
PRICE_CURRENT	−0.0170*** (0.0022)	0.0244*** (0.0057)	0.0332* (0.0184)
PRICE_PREVIOUS	−0.0047*** (0.0015)	0.0012 (0.0039)	−0.0913*** (0.0124)
AVAILABLE_CURRENT	0.5002*** (0.0240)	−0.9902*** (0.0617)	−0.3079 (0.1972)
AVAILABLE_CURRENT_SQ	−0.0499*** (0.0026)	0.1026*** (0.0067)	0.2753*** (0.0214)
SUN	0.0006 (0.0007)	−0.0015 (0.0017)	−0.0044 (0.0054)
MON	0.0008 (0.0006)	−0.0025 (0.0017)	−0.0024 (0.0056)
TUE	0.0007 (0.0007)	−0.0026 (0.0017)	−0.0003 (0.0055)
WED	0.0006 (0.0006)	−0.0031* (0.0018)	−0.0019 (0.0054)
THU	0.0007 (0.0007)	−0.0026 (0.0017)	−0.0015 (0.0055)
FRI	0.0001 (0.0006)	−0.0009 (0.0017)	−0.0006 (0.0054)
MARCH	−0.0142*** (0.0030)	0.0348*** (0.0077)	0.1510*** (0.0246)
APRIL	−0.0087*** (0.0024)	0.0191*** (0.0064)	0.1037*** (0.0204)
MAY	−0.0031 (0.0019)	0.0119** (0.0050)	0.0809*** (0.0160)
JUNE	−0.0019 (0.0015)	0.0103*** (0.0039)	0.1051*** (0.0126)
JULY	−0.0030 (0.0013)	0.008** (0.0034)	0.0454*** (0.0111)
WEATHER	−0.0054*** (0.0016)	0.0149*** (0.0041)	0.1324*** (0.0133)
Number of observations	8,374	8,374	8,374
R^2	0.9114	0.8121	0.9905
PRODUCT fixed effects	Yes	Yes	Yes

Note. PRODUCT fixed effects are not reported.
[a]The dependent variables are the valence, standard deviation, and volume measures for the online reviews.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 3. First-Stage Estimates for Endogenous Variables (Previous Generation)

	Endogenous variables		
	VALENCE_PREVIOUS[a]	*STDEV_PREVIOUS*[a]	*VOLUME_PREVIOUS*[a]
INSTRUMENT for VALENCE_PREVIOUS	0.1053*** (0.0093)	0.0516*** (0.0170)	−1.9453*** (0.0697)
INSTRUMENT for STDEV_PREVIOUS	−0.1425*** (0.0046)	0 0.2702*** (0.0084)	−0.8980*** (0.0347)
INSTRUMENT for VOLUME_PREVIOUS	0.0177*** (0.0006)	0.0002 (0.0012)	0.1943*** (0.0049)
INSTRUMENT for VALENCE_CURRENT	−0.0144*** (0.0030)	0.0317*** (0.0055)	−0.3781*** (0.0227)
INSTRUMENT for STDEV_CURRENT	−0.0139*** (0.0003)	0.0232*** (0.0006)	−0.0517*** (0.0026)
INSTRUMENT for VOLUME_CURRENT	−0.0176*** (0.0006)	0.0008 (0.0011)	−0.1877*** (0.0046)
PRICE_CURRENT	−0.0019*** (0.0003)	0.0052*** (0.0006)	−0.0370*** (0.0024)
PRICE_PREVIOUS	0.0001 (0.0002)	−0.0003 (0.0004)	0.0062*** (0.0016)
AVAILABLE_PREVIOUS	0.4022*** (0.0229)	−0.6330*** (0.0416)	5.5656*** (0.1707)
AVAILABLE_PREVIOUS_SQ	−0.0320*** (0.0019)	0.0484*** (0.0034)	−0.3944*** (0.0143)
SUN	0.0001 (0.0001)	−0.0001 (0.0002)	−0.0001 (0.0007)
MON	0.0001 (0.0001)	−0.0001 (0.0001)	−0.0003 (0.0007)
TUE	0.0003 (0.0002)	−0.0001 (0 0.0002)	−0.0004 (0.0007)
WED	−5.75e-06 (0.0001)	−0.0000 (0.0001)	−0.0005 (0.0007)
THU	−5.86e-06 (0.0001)	−0.0001 (0.0001)	−0.0002 (0.0007)
FRI	−0.0001 (0.0001)	−0.0000 (0.0002)	−0.0004 (0.0008)
MARCH	−0.0008* (0.0005)	0.0009 (0.0008)	−0.0057* (0.0035)
APRIL	−0.0007** (0.0003)	0.0009 (0.0007)	−0.0071** (0.0029)
MAY	−0.0002 (0.0003)	0.0001 (0.0006)	−0.0066*** (0.0022)
JUNE	−0.0005** (0.0002)	0.0011** (0.0005)	−0.0049*** (0.0019)
JULY	−0.0001 (0.0002)	0.0006 (0.0004)	−0.0013 (0.0015)
WEATHER	−0.0008*** (0.0003)	0.0010** (0.0005)	−0.0069*** (0.0020)
Number of observations	8,374	8,374	8,374
R^2	0.9979	0.9972	0.9993
PRODUCT fixed effects	Yes	Yes	Yes

Note. PRODUCT fixed effects are not reported.
[a]The dependent variables are the valence, standard deviation, and volume measures for the online reviews.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

evaluation, including consulting reviews for the previous generation. Third, when the current generation product has been *available* for a long period of time, we expect previous generation valence to matter less. The rationale is that, in general, the greater the duration for which the current generation has been available in the market, the greater the number of sources from which consumers can obtain information about that specific product. As a result, consumers will be less reliant on previous generation reviews when evaluating the current generation product. Finally, the positive carryover of previous generation valence should also decrease to

Table 4. Impact of Previous Generation Reviews on Current Generation Sales

	Dependent variable = log(*CURRENT SALES RANK*)[a]	
	Without endogeneity correction	With endogeneity correction (instrumental variables)
VALENCE_CURRENT	−0.3606	−10.9832***
	(0.5441)	(2.0504)
VALENCE_PREVIOUS	−18.9935***	−70.4633***
	(3.1183)	(21.8925)
STDEV_CURRENT	0.1325	−5.9958***
	(0.1818)	(0.8673)
STDEV_PREVIOUS	−10.3276***	−45.1727***
	(2.0884)	(8.4484)
VOLUME_CURRENT	−0.2634***	−1.6185***
	(0.0407)	(0.2399)
VOLUME_PREVIOUS	−2.9117***	−2.2079
	(0.3934)	(1.6886)
PRICE_CURRENT	3.3078***	3.4169***
	(0.0667)	(0.0807)
PRICE_PREVIOUS	−0.1376***	−0.3497***
	(0.0401)	(0.0457)
COMPETITION_VALENCE_OWN	2.9027***	3.0540***
	(0.6707)	(0.5051)
COMPETITION_VALENCE_OTHER	0.2175	1.1472***
	(0.2199)	(0.3551)
NEW_PRODUCTS	0.0462***	−0.0007
	(0.0134)	(0.0259)
AVAILABLE_CURRENT	−7.3130***	−8.4066***
	(0.9196)	(1.5354)
AVAILABLE_CURRENT_SQ	0.9912***	1.4617***
	(0.0943)	(0.1637)
MARCH	0.1062	0.5176***
	(0.0979)	(0.0862)
APRIL	0.0469	0.3521***
	(0.0807)	(0.0792)
MAY	0.0130	0.1661***
	(0.0577)	(0.0558)
JUNE	0.1261**	0.3802***
	(0.0555)	(0.0598)
JULY	0.0841**	0.2093***
	(0.0398)	(0.0520)
WEATHER	0.1717***	0.4164***
	(0.0436)	(0.0682)
Number of observations	8,374	8,374
R^2	0.8703	0.8375
PRODUCT fixed effects	Yes	Yes

Note. *PRODUCT* fixed effects are not reported and *DAY OF THE WEEK* fixed effects are not reported.
[a]The dependent variable is the current generation sales rank.
**$p < 0.05$; ***$p < 0.01$.

Table 5. Impact of Current Generation Reviews on Previous Generation Sales

	Dependent variable = log(*PREVIOUS SALES RANK*)[a]	
	Without endogeneity correction	With endogeneity correction (instrumental variables)
VALENCE_CURRENT	4.5960***	7.795***
	(0.4903)	(1.6114)
VALENCE_PREVIOUS	−51.1137***	−195.2786***
	(4.9987)	(31.6260)
STDEV_CURRENT	1.8499***	−1.1485
	(0.2171)	(1.5400)
STDEV_PREVIOUS	−15.3884***	−74.1142***
	(3.0676)	(18.3996)
VOLUME_CURRENT	−1.1684***	0.0207
	(0.0742)	(0.3485)
VOLUME_PREVIOUS	−0.7689*	3.1835***
	(0.4380)	(1.1467)
PRICE_CURRENT	0.0226	0.2336
	(0.1253)	(0.1549)
PRICE_PREVIOUS	−0.2082***	−0.1830***
	(0.0648)	(0.0654)
COMPETITION_VALENCE_OWN	0.8878	2.6001***
	(0.5609)	(0.6202)
COMPETITION_VALENCE_OTHER	−0.6581**	−1.3063***
	(0.3111)	(0.2564)
NEW_PRODUCTS	−0.1399***	−0.1086***
	(0.0267)	(0.0274)
AVAILABLE_PREVIOUS	53.5906***	20.5725*
	(6.9568)	(11.4892)
AVAILABLE_PREVIOUS_SQ	−4.0217***	−1.9817**
	(0.5939)	(0.8179)
MARCH	0.2969***	0.2159
	(0.1051)	(0.1529)
APRIL	0.2575***	0.1830
	(0.0976)	(0.1285)
MAY	0.0525	0.0372
	(0.0739)	(0.1247)
JUNE	0.1683**	0.1425
	(0.0699)	(0.1022)
JULY	0.1067	0.1368
	(0.0655)	(0.1008)
WEATHER	−0.3425***	−0.3446***
	(0.1039)	(0.0765)
Number of observations	8,374	8,374
R^2	0.7268	0.7248
PRODUCT fixed effects	Yes	Yes

Note. *PRODUCT* fixed effects are not reported and *DAY OF THE WEEK* fixed effects are not reported.
[a]The dependent variable is the current generation sales rank.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

the extent that *uncertainty in previous generation reviews* is high. The logic is similar to Sun (2012) (i.e., uncertainty (because of an increase in the standard deviation of ratings) reduces the positive impact of high valence by driving away the marginal consumers).

Next, we focus on two key moderators for previous generation sales. First, when the *current generation valence* is high, one would expect stronger substitution of the current generation for the previous generation. One consequence of this is that the positive impact of previous generation valence should be attenuated. Second, when the *release gap* between the two product generations is large, we expect current generation valence to matter more. This is consistent with the idea that a longer release gap suggests greater improvements to the current generation product compared with the previous generation product. In this situation, a high current review valence will make the previous generation even less appealing and the substitution effect stronger. To examine the moderating effects of these factors, we specify the current and previous generation models as follows:

$$\begin{aligned}
&\log(CURRENT\ SALES\ RANK_{it})\\
&\quad = \lambda_i^C + \delta_1^C \log(PRICE_CURRENT_{it-1})\\
&\qquad + \delta_2^C \log(PRICE_PREVIOUS_{it-1})\\
&\qquad + \delta_3^C \log(VALENCE_CURRENT_{it-1})\\
&\qquad + \delta_4^C \log(VALENCE_PREVIOUS_{it-1})\\
&\qquad + \delta_5^C \log(STDEV_CURRENT_{it-1})\\
&\qquad + \delta_6^C \log(STDEV_PREVIOUS_{it-1})\\
&\qquad + \delta_7^C \log(VOLUME_CURRENT_{it-1})\\
&\qquad + \delta_8^C \log(VOLUME_PREVIOUS_{it-1})\\
&\qquad + \delta_9^C \log(COMPETITION_VALENCE_OWN_{it-1})\\
&\qquad + \delta_{10}^C \log(COMPETITION_VALENCE_OTHER_{it-1})\\
&\qquad + \delta_{11}^C \log(NEW_PRODUCTS_{it-1})\\
&\qquad + \phi_1^C \log(VALENCE_PREVIOUS_{it-1})\\
&\qquad \times \log(STDEV_CURRENT_{it-1})\\
&\qquad + \phi_2^C \log(VALENCE_PREVIOUS_{it-1})\\
&\qquad \times \log(VALENCE_CURRENT_{it-1})\\
&\qquad + \phi_3^C \log(VALENCE_PREVIOUS_{it-1})\\
&\qquad \times \log(AVAILABLE_CURRENT_{it-1})\\
&\qquad + \phi_4^C \log(VALENCE_PREVIOUS_{it-1})\\
&\qquad \times \log(STDEV_PREVIOUS_{it-1})\\
&\qquad + \delta_{12}^C \log(AVAILABLE_CURRENT_{it-1})\\
&\qquad + \delta_{13}^C \log(AVAILABLE_CURRENT_SQ_{it-1})\\
&\qquad + \delta_{14}^C \log(WEATHER_{it}) + \Pi^C(D_{it}) + \Upsilon^C(M_{it}) + \xi_{it}^C
\end{aligned} \tag{3}$$

$$\begin{aligned}
&\log(PREVIOUS\ SALES\ RANK_{it})\\
&\quad = \lambda_i^P + \delta_1^P \log(PRICE_CURRENT_{it-1})\\
&\qquad + \delta_2^P \log(PRICE_PREVIOUS_{it-1})\\
&\qquad + \delta_3^P \log(VALENCE_CURRENT_{it-1})\\
&\qquad + \delta_4^P \log(VALENCE_PREVIOUS_{it-1})\\
&\qquad + \delta_5^P \log(STDEV_CURRENT_{it-1})\\
&\qquad + \delta_6^P \log(STDEV_PREVIOUS_{it-1})\\
&\qquad + \delta_7^P \log(VOLUME_CURRENT_{it-1})\\
&\qquad + \delta_8^P \log(VOLUME_PREVIOUS_{it-1})\\
&\qquad + \delta_9^P \log(COMPETITION_VALENCE_OWN_{it-1})\\
&\qquad + \delta_{10}^P \log(COMPETITION_VALENCE_OTHER_{it-1})\\
&\qquad + \delta_{11}^P \log(NEW_PRODUCTS_{it-1})\\
&\qquad + \phi_1^P \log(VALENCE_PREVIOUS_{it-1})\\
&\qquad \times \log(VALENCE_CURRENT_{it-1})\\
&\qquad + \phi_2^P \log(VALENCE_CURRENT_{it-1})\\
&\qquad \times \log(RELEASE_GAP_{it-1})\\
&\qquad + \delta_{12}^P \log(AVAILABLE_PREVIOUS_{it-1})\\
&\qquad + \delta_{13}^P \log(AVAILABLE_PREVIOUS_SQ_{it-1})\\
&\qquad + \delta_{14}^P \log(WEATHER_{it}) + \Pi^P(D_{it}) + \Upsilon^P(M_{it}) + \xi_{it}^P.
\end{aligned} \tag{4}$$

Results appear in Tables 6 and 7. R^2 statistics do not change dramatically with the addition of the interaction terms. However, as is known (e.g., Maddala 1992), R^2 numbers are not appropriate as a measure of fit and model selection in an IV context. Because our objective in this study is to accurately describe the nature of the relationships between certain key variables rather than prediction, we focus on the moderating effects that add new insights to the analysis. Specifically, we find strong evidence in the form of the *p*-values on the interaction terms in which moderating effects are present. These have important managerial implications, which we discuss later. In Table 6, we find that the positive impact of previous generation valence becomes *stronger* as the uncertainty in current generation reviews (standard deviation) increases and when the current generation valence is high. In contrast, this influence becomes *weaker* as the uncertainty in previous generation reviews (standard deviation) increases and as the duration for which the current generation is available increases. For the previous generation model in Table 7, we find that the substitution effect associated with current generation valence increases as the release gap between the two generations increases. In addition, the positive impact of previous generation valence decreases as the current generation valence increases.

Online Appendix B contains a number of different robustness checks. In particular, we repeat the analysis using different lag periods (two periods and three periods) and considering only the most recent month of review activity for the current and previous generations. In all cases, the key results are qualitatively similar to the main analysis.

Discussion and Conclusion

The literature on online word of mouth has developed rapidly in a short period of time. Despite the many insights in this literature, to the best of our knowledge, no study has examined the influence of reviews for

Table 6. Key Moderators: Current Generation Model

	Dependent variable = log(*CURRENT SALES RANK*)[a]
	With endogeneity correction (instrumental variables)
VALENCE_PREVIOUS	32.9971*** (7.9218)
VALENCE_CURRENT	269.6342** (111.6603)
STDEV_CURRENT	178.7529*** (49.7173)
STDEV_PREVIOUS	−507.1824** (252.5610)
VOLUME_CURRENT	−2.0255*** (0.4433)
VOLUME_PREVIOUS	−3.3928 (2.2286)
PRICE_CURRENT	3.5088*** (0.1192)
PRICE_PREVIOUS	−0.3241*** (0.0606)
COMPETITION_VALENCE_OWN	3.8943*** (0.8264)
COMPETITION_VALENCE_OTHER	0.5539** (0.2742)
NEW_PRODUCTS	0.0081 (0.0188)
AVAILABLE_CURRENT	−10.6263*** (2.0003)
AVAILABLE_CURRENT_SQ	0.9501*** (0.1937)
VALENCE_PREVIOUS × *STDDEV_CURRENT*	−111.5369*** (31.6756)
VALENCE_PREVIOUS × *STDEV_PREVIOUS*	285.9533** (149.7774)
VALENCE_PREVIOUS × *VALENCE_CURRENT*	−172.4946** (72.4689)
VALENCE_PREVIOUS × *AVAILABLE_CURRENT*	4.7705*** (1.7145)
MARCH	0.3630*** (0.1031)
APRIL	0.2514*** (0.0941)
MAY	0.1087* (0.0562)
JUNE	0.2654*** (0.0601)
JULY	0.1399*** (0.0504)
WEATHER	0.2840*** (0.0610)
Number of observations	8,374
R^2	0.8364
PRODUCT fixed effects	Yes

Note. PRODUCT fixed effects are not reported and *DAY OF THE WEEK* fixed effects are not reported.
[a]The dependent variable is the current generation sales rank.
$*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

one product generation on the sales of another. Many successful products are part of a product series. As companies continue to allocate more resources toward the management of online word of mouth, understanding the intergenerational influence of reviews has become a critical issue. Intergenerational reviews are unique in that they both speak to the overall features and performance of the product series as it competes against offerings from other brands and to the merits of one generation in the series as it competes against another. Therefore, reviews for one generation can either complement the sales of another generation or lead to the substitution of one generation for another. In this research, we show that this intergenerational influence is quite strong, especially when considering the impact of previous generation reviews on current generation sales. Failure to consider the influence of previous generation reviews results in an underappreciation of the importance of product reviews as a whole on the sales of products in a generational series.

Among the central findings is an asymmetry in the influence of reviews when moving forward versus backward through product generations that has not been observed before. We find that although previous generation review valence complements current generation sales, current generation review valence drives substitution of the current generation for the previous generation. Although our finding is strictly empirical, it is consistent with an "always buy new" mindset in which consumers observe that features and performance tend to build in technology products over time. As a result, they may come to see positive aspects of the previous generation as likely to carry over to the current generation, whereas positive aspects of the current generation will not necessarily carry back to the previous generation. In addition, the complementarity between previous generation reviews and current generation sales may come about in part because critical differentiating features relative to competing brands emerge in the reviews for early generations, whereas later generation reviews may focus more on the comparison between generations within the series. Our results also show that reviews of the previous generation differ from reviews of competing products of other brands—and competing offerings of the same brand outside the series—the valences of which are negatively related to sales of the current generation.

We also uncover a number of factors that moderate the relationships described. Reviews of the previous generation play a larger role in determining the sales of the current generation as the uncertainty surrounding the reviews of the current generation increases. This is consistent with the longstanding view that consumers look for other sources of information in this situation to resolve the lack of consensus. The positive impact of previous generation valence also becomes more positive as the valence of the current generation increases. We attribute this to the current generation advancing deeper into the consideration process, at which point greater elaboration leads to more in-depth processing of previous generation reviews, although our data do not allow insight into the precise mechanisms underlying the relationship. We also identify two factors that diminish the complementarity between previous generation reviews and current generation sales. As a corollary to the finding, an increase in the uncertainty of previous generation reviews decreases the positive impact of previous generation valence. In addition, previous generation valence is less impactful when the current generation product has been available for a long period of time and other sources of information become available.

When examining sales of the previous generation, we find two new insights. First, as current generation valence increases, the positive impact of previous generation valence on previous generation sales decreases because a stronger substitution effect attenuates the influence of previous generation reviews. Second, as the release gap between the two generations increases, the substitution effect of current generation reviews on previous generation sales increases. One explanation for this effect is that a larger release gap suggests a greater improvement in the current generation, making the previous generation less attractive and enhancing the strength of the substitution effect away from it.

Managerial Implications

Our study has important implications for managers because it uncovers a number of effects of reviews across product generations that were previously unknown. First and most fundamentally, our results show that it is more important to manage online word of mouth for products in a generational series. This is because the reputation garnered by one generation has carryover effects on subsequent products in the same series. This carryover creates an attribution problem when measuring and valuing online customer reviews that must be recognized by managers. The effects of reviews for one generation do not stop with the introduction of a new generation. Consequently, positive reviews are more valuable—and negative reviews more harmful—than their effects on own-generation sales would suggest. Managers must therefore consider the impact of reviews for multiple generations when assessing word of mouth for a given product or evaluating the performance of initiatives to enhance the sentiment of reviews.

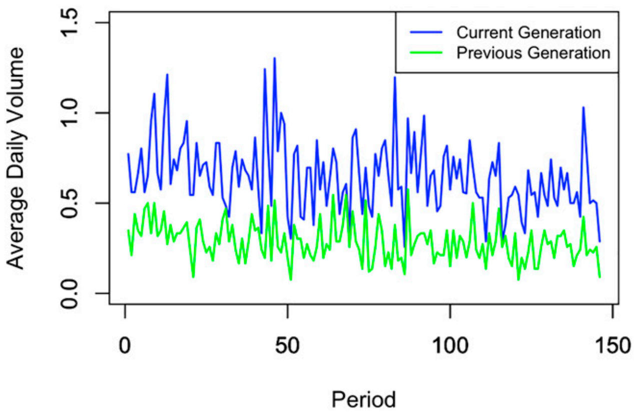
Second, the results point to the usefulness of continuing to manage and stimulate reviews for older generations of the product as well as the latest generation when both products overlap in the new product

Table 7. Key Moderators: Previous Generation Model

	Dependent variable = log(*PREVIOUS SALES RANK*)[a]
	With endogeneity correction (instrumental variables)
VALENCE_PREVIOUS	−371.6814***
	(37.1859)
VALENCE_CURRENT	−464.8156***
	(49.4743)
STDEV_CURRENT	5.7343***
	(0.5806)
STDEV_PREVIOUS	−14.5128***
	(3.8013)
VOLUME_CURRENT	−0.2705
	(0.1911)
VOLUME_PREVIOUS	−2.4259*
	(1.0670)
PRICE_CURRENT	−0.0597
	(0.1246)
PRICE_PREVIOUS	−0.1375*
	(0.0762)
COMPETITION_VALENCE_OWN	0.4483
	(0.5726)
COMPETITION_VALENCE_OTHER	−0.4407**
	(0.2190)
NEW_PRODUCTS	−0.1145***
	(0.0296)
AVAILABLE_PREVIOUS	52.6178***
	(10.8135)
AVAILABLE_PREVIOUS_SQ	−4.0683***
	(0.8538)
VALENCE_CURRENT × *RELEASE GAP*	28.0337***
	(5.0998)
VALENCE_PREVIOUS × *VALENCE_CURRENT*	193.8242***
	(22.6613)
MARCH	0.2434*
	(0.1317)
APRIL	0.1846*
	(0.1089)
MAY	0.0459
	(0.0858)
JUNE	0.1172*
	(0.0692)
JULY	0.0813
	(0.0706)
WEATHER	−0.3346***
	(0.0878)
Number of observations	8,374
R^2	0.7254
PRODUCT fixed effects	Yes

Note. *PRODUCT* fixed effects are not reported and *DAY OF THE WEEK* fixed effects are not reported.
[a]The dependent variable is the previous generation sales rank.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Figure 4. (Color online) Average Daily Review Volume for Current (Top Line) and Previous (Bottom Line) Generations



market. In Figure 4, we show the average daily volume of reviews for the current and previous generations in each product pair. As can be seen, although the current generation receives more reviews, the previous generation is subject to a surprisingly high level of review activity. Because sales of the current generation are aided by the complementary effect of these previous generation reviews, firms that encourage positive reviews for previous generations while they are still on the market can realize stronger sales of their current generation product. Managers may be reticent to promote such reviews because (a) the previous generation competes with the current generation, typically at a lower price, and (b) the selection of the previous generation over the current generation is likely to be mentioned explicitly in the review after the latter is on the market. However, our results suggest that such a mindset is unwarranted and that promoting reviews for the previous generation alongside the current generation can be beneficial. Interestingly, generating reviews for the previous generation is especially valuable at or near the launch of the current generation because previous generation reviews have their largest effect when the new generation has not been on the market very long.

Third, it is important for managers to understand the unexpected ways in which the valence of reviews can impact the processing of reviews for other generations. High valence for the current generation can lead to greater reliance on previous generation reviews. This means that successful product generations can build on each other, with the high valence of the current generation bringing positive reviews for the previous generation more into play. Maintaining consistently high reviews over time is critical to this virtuous cycle because strong current generation reviews will increase the influence of previous generation reviews. In contrast, the risk of a poorly reviewed generation is heightened in that an attempt to turn around a product series by introducing a higher-quality product (which generates positive reviews) may face headwinds because of the stronger influence of reviews for the poorly received previous generation.

Fourth, it is equally important for managers to understand the role of review uncertainty, in addition to the sentiment of reviews. Strong previous generations provide a degree of protection against equivocal reviews for a new generation because consumers will appeal to previous generation reviews when confronting uncertainty in current generation reviews. The same protection extends to new generations that have been on the market for only a short period of time. In each instance, consumers will turn more to previous generation reviews, and a strong previous generation is thus more valuable. This holds as long as the uncertainty surrounding the previous generation is not too high because this tends to diminish the impact of previous generation reviews. In contrast, if a company suffers a weak previous generation, it should do everything it can to support the generation of unequivocal reviews for its latest generation in order to discourage consumers from processing weak previous generation reviews to the same extent. Indeed, in this case, managers would ideally sacrifice some degree of valence *at the margin* for greater consistency in reviews for the new generation because this limits the shadow of the past cast by a poorly reviewed generation.

Fifth, extending the implications beyond the short-term time frame of the study, the results can help managers make decisions related to the degree of overlap between generations. Our findings make a solid case for an overlapping product series strategy in which the previous generation is kept on the market longer if it is well reviewed by consumers. Leaving the previous generation on the market will promote new reviews for it that, in turn, aid sales of the latest generation. In addition, a previous generation with a high rating gives more leeway for the firm to introduce a bolder next generation product. Even if the reviews are mixed (a potential by-product of a more ambitious new product), this will only increase the impact of the prior generation reviews and the support provided by their strong valence. Although new product development cycles are typically lengthy, this same insight can be applied to advertising campaigns and other aspects of the launch, which are formulated with a shorter lead time.

Finally, it is important to consider the role of sources of information other than online reviews. In particular, after products are on the market for a suitable period of time, there is a lesser role for previous generation reviews. This occurs in part because additional sources of information about the current generation become available. Hence, the more distant appeal to previous generation reviews is less necessary for consumers.

This suggests that as firms make more information available about the current generation, the impact of a disappointing previous generation decreases.

Limitations and Future Research

This is an initial investigation into the effects of intergenerational product reviews. As such, there are some limitations. We examined a single product category that was chosen because of the clear product series it contains. There are other categories in which the series nature of products is fairly pronounced (e.g., cell phones) that would serve as fertile ground for future research. It would also be informative to understand whether the results hold in categories where the series are not as apparent to consumers (e.g., televisions). Although reviews for previous generations should still matter in such categories, the effects may be weaker because the series are less salient.

We also focused on a product category in which multiple generations are offered in the new product market at the same time. We did this because we anticipated that new reviews would be created for both generations under roughly similar conditions (e.g., availability of manufacturer's warranties, ability to return products to the retailer). An extended investigation would consider intergenerational reviews more broadly, including contexts where previous generations are only available in the used product market. As noted, we would still expect reviews for previous generations to matter, even if they are off the market or available only in the used product market, although the effects may be weaker.

We further restricted our analysis to the current and previous generations in the product series. It would be interesting to study the role of reviews for more than two generations. Long series like the Apple iPhone provide an interesting context in that (1) a substantial momentum may be built up because many different generations have been reviewed and (2) the critical comparisons with other brands (in this case, the Samsung/Android bundle) may have occurred many generations back, with reviews for recent generations focused on improvements within the series.

There are also several opportunities to expand on the modeling framework. Similar to prior research, we treated price as exogenous because there is limited within-product variation. However, the price measures are potentially endogenous, and we encourage future researchers to find appropriate instruments for them. In addition, it should be possible to expand on the dynamic nature of the models. Specifically, it would be helpful from a managerial perspective to have a sense of how far in advance product ratings matter and understand the short-term versus long-term effects. Vector autoregression (VAR) persistence models are one approach to investigate this issue, or researchers could expressly model the review generation process as in Godes and Silva (2012) and Moe and Schweidel (2012). Finally, we present a reduced form model that is consistent with, but does not demonstrate, the underlying mechanisms in their entirety.

In addition to addressing the issues, we see several other attractive avenues for future research. First, it would be very interesting to see if reviews for one generation affect *reviews* for another generation in terms of their valence and/or content in a manner similar to what we observe for the effect of such reviews on product sales. One issue is whether the asymmetry observed in our study with respect to sales would manifest itself when examining review valence. If so, for example, the valence of new reviews for the previous generation would react in the opposite direction of the valence of reviews for the current generation. Another issue is whether the interesting results observed for current generation valence and variance would carry over to the review-review context; viz, would a high valence or variance in reviews for the current generation result in new reviews for this generation reflecting those of the previous generation more.

Second, relatedly, our study provides a clear illustration of the effect of review variance. Specifically, we show that consumers look to, or are influenced by, other sources of information (in this case, previous generation reviews) more when variance is high. It is also reasonable to assume that consumers will look more to sources of information beyond customer generated reviews in this situation, such as advertising, salespeople, and expert reviews. Understanding these dynamics would greatly clarify the mixed findings uncovered for review variance in the literature.

Third, it would be interesting to examine how the effects uncovered in our study differ for high-selling versus low-selling brands. On one hand, purchases of high-selling brands are more likely to be made by consumers with direct experience with the previous generation, which may limit their need to reference previous generation reviews when making a purchase decision. This would suggest a lesser effect of previous generation reviews for strong selling products. On the other hand, high-selling brands are likely to receive greater consideration and elaboration, suggesting the possibility of an expanded role for previous generation reviews, like we observe for current generation valence in the present study.

Fourth, the interrelationships uncovered in this study may extend beyond the product pair. One fruitful avenue for research would be to examine how reviews across an entire product line jointly affect sales. This would be especially interesting for brands that compete in different product categories (e.g., how are the sales of cameras from a given brand affected by reviews for its phones and televisions). Because a brand that is well reviewed in one category can lead to greater sales in a second category, it is possible that reviews would be largely complementary across product categories in their effect on current generation products even though we show mostly substitution effects in the present study, except for the previous generation in the product series. Thus, for a focal current generation product, reviews for its predecessor in the series would be complementary, reviews for other products from the brand in the same category but outside the series would drive substitution, and reviews for products of the brand in other categories would again be complementary. It would also be interesting to examine whether the closeness of the product categories matters and how current and previous generation reviews within and outside the product category differ in their relationship to sales of the current or previous generation of a focal product pair.

Finally, reviews contain information about both product quality and product-consumer interaction factors, as noted. It would be interesting to explore the weights or importance of these different product-consumer factors such as fit and reliability, as evidenced by review text, in the decisions made by prospective consumers.

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Endnotes
[1] We acknowledge that this assumption is not well suited to every product category. Product series in the motion picture industry (i.e., sequels) are an example where this assumption is unlikely to hold. In addition, new models are occasionally introduced to "down market" a brand, although these models are not usually part of the same *series*. It is important to emphasize that we study identifiable product series, not simply the latest offering from a given brand.

[2] There are other time-varying factors as well such as consumer experiences with the product, which can be classified as product-consumer interaction factors. These product-consumer factors are time varying because the segment of consumers who buy the product changes over time. One example of a product-consumer factor is product fit. The extent of product fit changes over time depending on the match between the product features and the preferences of customers who buy the product at different points in time. Another important product-consumer factor is reliability, which broadly captures changes in product quality over time and also depends on the usage patterns of the evolving customer base. Reviews only partially capture these factors because only a small proportion of the customer base posts reviews.

[3] To investigate within-product price variation, we calculated the average daily percentage change in price for each camera and examined its distribution. The 5% and 95% quartiles are both within ±6%, illustrating the limited within-product price variation.

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