Revealed Preference in Online Reviews: Purchase Verification in the Tablet Market

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Abstract

The review systems of online platforms create a stream of online word-of-mouth that allows consumers to learn from others' purchasing experience. However, it is difficult for consumers to discern the authenticity of a review or the reviewer's level of experience with the product. Platforms can aid the authentication process by incorporating a verified purchase (VP) indication, or "badge" as is done on Amazon, in reviews where the consumer writing the review has verifiably purchased the focal product. A VP is a revealed preference for a product implying a utility-maximizing choice where the consumer writing the review has experience with the product. Combining an Amazon dataset on tablet computers with the theory of revealed preference in online reviews, we uncover a surprising new result: the proportion of VP reviews (a revealed preference) is associated with higher future sales, and the effect of the proportion of VP reviews on sales dominates the effect of the mean rating. This novel use of VP with revealed preference theory has implications for new research in the design of recommendation systems, detecting fraudulent reviews, and online profiling/privacy. Moreover, the use of a VP badge is immediately applicable to firms and platforms.

Keywords: revealed preference, product review, online word-of-mouth, verified purchase, platform strategy, trust

1. Introduction

A common idiom in the English language is "talk is cheap": it is easier to say you will do something than it is to do it. Another is "actions speak louder than words", which emphasizes that what you do shows your intentions more clearly than what you say. Yet a third is "put your money where your mouth is" which paraphrased is to show your intentions by your actions and choices, not just your words. The consistent theme is that true preferences are revealed by actions and choices, and that they carry more weight than words.

The theory of revealed preference developed by Samuelson [35, 36] is that an individual's preferences over alternatives give rise to a utility function of which the individual may not be aware. Regardless of their awareness, an individual's choices between alternatives implies a maximized utility function that in turn represents their preferences. Consequently, the theory suggests that an individual's true preferences can be best revealed by choices or actions that they take. We carry this idea, embedded in modern choice theory, into the realm of online product reviews and online word of mouth (OWOM). A survey conducted by Nielsen [30] reports that 66% of respondents trust OWOM posted by other consumers, behind only recommendations from people they know in earned media (85%) and branded websites in owned media (70%). Despite questions about the authenticity of online reviews, this high rate of trust persists. Non-authentic reviews are reviews written by the seller, a competitor, or a paid reviewer. We consider the number of reviews written by consumers that have revealed their preferences by purchasing a product – making a choice to maximize utility by purchasing the product – has a greater impact on sales and prices than reviews from non-purchasing consumers or even mean ratings within the reviews because it represents an authentic tangible demand for the product. Aggregating these purchase choices reveals preferences of the review population. Moreover, a consumer's verified purchase review reflects actual experience with the product – experience not all reviewers have - making their reviews more credible and trustworthy. Kokkodis and Lappas [22] find that consumers perceive verified purchase reviews as more helpful. On the other hand, Anderson and Simester [1] show that reviews by customers without purchase are less likely to describe how items fit or feel and more likely to contain deceptive linguistic cues.

In 2009, Amazon.com (hereafter Amazon) introduced a new feature for customer reviews: Amazon Verified Purchase.[1] This feature labels the review with a verified purchase (VP) badge (see Figure 1) if the reviewer bought the product on Amazon. Amazon believes that purchase verification "offers Amazon.com customers additional context and helps them better gauge the quality and relevance of a product review... customers can look at [the VP] label to decide which reviews can help them make their purchasing decisions."[2] Initial responses to the VP badge on Amazon's online forum were mixed. Some consumers valued the VP feature very highly, while others doubted it would make a difference. Similar review credibility systems have been adopted by other marketplaces, including Expedia.com (Expedia) and Orbitz.com. Expedia went so far as to only allow guests to post their reviews online (via Expedia Verified Reviews) if they had booked the hotels through the Expedia website.[3] However, not all marketplaces have followed the VP route. TripAdvisor.com (TripAdvisor), the world's largest travel platform [41] and Expedia's top rival, decided not to impose any verification of purchase process on its online posts. According to company spokesperson Kevin Carter, TripAdvisor has

"elected to use [its] current model for one simple reason: The volume of opinions provides for the most in-depth coverage of consumer experience, and it is the model that consumers prefer," [4]

although no evidence was offered to support these claims. In fact, the UK Advertising Standards Authority (ASA) once ruled against TripAdvisor (UK site) to cease using misleading phrases like

"*Reviews you can trust*", "*... read reviews from real travellers*", and "*TripAdvisor offers trusted advice from real travellers*".[5]

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[1] https://www.amazon.com/gp/community-help/amazon-verified-purchase
[2] https://www.amazon.com/forum/top%20reviewers?cdForum=Fx2Z5LRXMSUDQH2&cdSort=oldest&cdThread=Tx2Q81WBNDUSS3W
[3] https://www.tnooz.com/article/goodbye-tripadvisor-welcome-to-verified-reviews-on-expedia
[4] https://skift.com/2015/07/28/tripadvisors-reviews-wont-change-even-as-it-becomes-the-next-big-booking-site
[5] https://www.asa.org.uk/rulings/tripadvisor-llc-a11-166867.html#U496yuhupLR (accessed August 25, 2018).

In this research we use a unique dataset of online reviews and market dynamics from Amazon to investigate the effect of the VP badge on sales in the tablet computer market – a prototypical high technology product. Connecting our work to the theory of revealed preference, we take it that a consumer shopping for a tablet computer establishes a choice set where products and merchants in the choice set implicitly have combinations of attributes. A purchase from this choice set reveals a utility-maximizing preference for the product and the merchant, and is a VP. Future consumers consider that they may have the same preferences to those of consumers that came before and take the VP as a signal that the product-merchant was utility-maximizing.

Our study makes several novel contributions. To the best of our knowledge, this is the first study that examines the direct effects of purchase verification on both product sales and price. Our results are based upon the classic but underutilized theory of revealed preference in prediction: consumers having purchased a product among different alternatives and the information that conveys about demand can explain future sales and price. We show that reviews written by consumers with a verified purchase have greater explanatory power in predicting future sales and price than the mean review rating. Our results also highlight a promising and immediately applicable action for e-commerce platforms: Implementing purchase verification is straightforward, helping address the authenticity issue of online reviews and reflecting reviewer's real experience using the product. Displaying purchase verification status along with online reviews could also increase the associated trustworthiness as this verification is an endorsement from the platform about the reviewers. Our study is a good indicator for platforms debating the adoption of a VP badge, and opens the gate for future research into the nature of VP reviews such as how they differ systematically from non-VP reviews in the content of review text. The results also encourage the development of new rating algorithms that incorporate such information. Amazon has already taken this step forward to surface newer and more helpful reviews.[6]

Next, we review the existing literature on OWOM's effects on product and firm performances, concerns and manipulations regarding OWOM, and trust associated with OWOM. In section 3, we describe our data. We present our empirical approach in section 4, followed by our main results in section 5. We discuss our results and limitations in section 6.

2. Literature Review

Word-of-mouth (WOM) shapes consumers' opinions and affects their actions; it serves as an important source of information for interested consumers to infer the quality of the product, thereby partially resolving information asymmetries between sellers and consumers [2]. As a special subtype of general WOM, OWOM flourished with the boom of the Internet. OWOM carries two distinct advantages: (1) it comes at minimal or zero cost with unprecedented scale, and (2) it is easily accessible to global Internet users. Resnick and Zeckhauser [33] point out that the low (almost zero) cost to provide evaluations on the Internet enables OWOM to substitute for the much more reliable yet limited mode of traditional WOM with a much better distribution of user-generated content. In addition, Dellarocas [8] credited scale of Internet distribution as the key element of OWOM effectiveness. Online sellers consider consumer feedback because of retention rates. With easy accessibility to every Internet user, OWOM also helps to transfer information through weak ties and penetrate social barriers (e.g., those between different communities or groups) to reach more audiences [15].

Previous literature has established the importance and effects of OWOM by showing associations with firm performance measures in many industries such as the rating of new television shows [13], digital camera sales on Amazon [17], movie box office sales [9, 25], book sales on Amazon [7, 24, 40], hotel bookings [44], restaurant sales [26], price of MP3 players [38], and channel disintermediation on

[6] https://www.cnet.com/news/amazon-updates-customer-reviews-with-new-machine-learning-platform/

information goods [23]. One channel of such impacts is the complimentary effects of OWOM on advertising which can boost new product demand with more power in the later stage of a product's life cycle [5]. Godes [12] shows how increased OWOM informs consumers about the product's quality which increases the elasticity of demand with respect to quality, and the optimal firm response to this increased elasticity is to improve quality. Using restaurant review data from China, Wu et al. [43] estimate that the economic value of restaurant reviews is close to ¥10 (≈$1.50) for each visitor from a better dining decision with reduced uncertainty contributing to a visitor's utility and for the restaurants from additional profit from each visitor.

Extant research has clearly documented the effects of several important review characteristics. Firstly, OWOM volume and ratings have been shown to affect sales and other performance measures. For example, Liu [25] concludes that most of the explanatory power on sales comes from OWOM volume, and a similar effect has been reported in Powell et al. [32] whereby consumers tend to favor products with a large number of reviews. Gopinath et al. [14] show that valence (a construct that includes rating) is directly related to sales and that the effects increase over time. Effects of salience of valence have also been investigated. Both positive and critical ratings are shown to boost sales as they could reduce consumer uncertainty of the product. On one hand, reviews with higher product ratings are shown to increase sales [7]. On the other hand, reviews that are critical can increase product awareness, thus leading to more purchases for niche products [4]. One possible reason could be due to the confirmation bias that consumers favor the reviews that confirm their initial belief [45, 18]. Secondly, the anonymity of OWOM reviewers creates a unique issue related to authenticity. Consumers frequently resort to various WOM sources in search of authentic reviews. Zhou and Duan [47] investigate a model in which online user reviews mediate the impact of professional reviews on online user decisions. Mayzlin [28] shows that anonymity allows firms to directly manipulate consumer-to-consumer conversations; It also allows firms with lower quality goods to engage in more promotional chat by posing as consumers. Luca and Zervas [27] identify a similar pattern of WOM manipulation occurs in the restaurant industry when a restaurant's reputation is poor, when there are very few posts, or when the level of competition is high. Thirdly, in light of non-authentic or manipulated reviews, consumers rely on both the source characteristics and the review content to evaluate review credibility. One of the two major dimensions of credibility is trustworthiness [20]. A meta-analysis of 51 studies about OWOM indicates that OWOM has a larger effect on sales if the messages are perceived as more trustworthy which is influenced by the relationship between OWOM sender and recipient [46]. Forman et al. [10] identify community norms as an antecedent to reviewer disclosure of identity-descriptive information. Disclosing such information reinforces the community norm, yields a higher level of peer recognition between reviewer and consumers, and consequently encourages trust. Therefore, a higher prevalence of reviews containing reviewer identity-descriptive information is associated with increased sales. Another meta-analysis on 96 studies yields a similar conclusion: Rosario et al. [34] find that OWOM with details allowing consumers to better assess their similarity to the OWOM author/sender is better linked to sales. And the effectiveness of OWOM is amplified by the sender trustworthiness details. Other reviewer-related signals also affect consumers' perception of the reviews. Siering et al. [39] find that reviews by more experienced reviewers and those disclosing their real name are perceived as reliable.

Purchase verification in online review reveals the reviewing consumers' actual choices which reflects their utility maximization, yielding true preferences over a selection of products [35, 36, 42]. These analyses based on revealed preference suggest that purchases made by preceding consumers reveal an aggregate preference over the choice set, and this aggregate preference together with the content of the reviews reflecting experience serves as a signal that shapes later consumers' opinion towards the reviewed/purchased product. Kaushik et al. [19] use percentage of VP reviews as a measure of review persuasiveness and estimate a positive association with sales rank on Amazon's platform for India's marketplace. Kim et al. [21] show some positive effects of VP reviews on movie box office revenue. Therefore, we hypothesize that implementing a transparent reviewer purchase verification mechanism has a positive impact on a product's sales. Accordingly, we focus on a subset of all reviews, the ones with verified purchase. These two studies differ with our study in several aspects. The biggest difference is the range of reviews. Kaushik et al. [19] limit the range to only helpful reviews on the product page while Kim et al. [21] cover all reviews. We, on the other hand, consider a more realistic scenario that consumers are unlikely to read all reviews if there are too many and likely to read more reviews than the first few shown on the product page.

The revealed consumers' utility-maximizing preferences could also impact firm decisions. Palou and Dimoka [31] discover that buyers on eBay.com (eBay) perceive sellers as more credible if they receive more text comments in the feedback about their past transactions. Consequently, sellers benefit from such higher trust by charging a price premium. Thus, we also hypothesize that enhancing trustworthiness by implementing reviewer purchase verification has positive impacts on a product's price, a decision made by the firm/seller.

To summarize, research has shown that OWOM has a critical impact on consumers' decision making. Although effects of purchase verification in online reviews have been examined, the studies are conducted either in a different industry (movie) or using a different outcome (helpfulness). The revealed utility-maximizing preference impacts both consumer and firm decision making. Therefore, our main hypothesis is that VP reviews positively impact product sales and price. A second and potentially more powerful hypothesis is that the effects of VP reviews are larger than effects of mean review rating.

3. Data

We utilize a dataset of tablet computers from Amazon where the intrinsic choice set in our data is the collection of all similar high-technology products in the tablet computer category. We view tablet computers as a prototypical high technology product where product evolution is rapid. This original data contains weekly observations of over 800 tablet products from February to July 2012. To investigate more modern tablets, whereby the first-generation iPad virtually redefined the tablet computer concept [16], we exclude products launched before the first-generation iPad release. We select the top 15 brands that covered more than 99% of the market share in 2012. These include Acer, Apple, Archos, Asus, Coby, Dell, HP, Le Pan, Lenovo, Motorola, Pandigital, Samsung, Toshiba, Velocity, and ViewSonic. The original dataset does not include Kindle Fire. These 15 brands are classified into three market share clusters based on shipments: high, medium, and low (see appendix Figure A1) - refining the choice set faced by consumers to those tablet computers that are likely to be in close competition. For example, the high-volume cluster contains only two brands, Apple and Samsung, the top two competitors in the tablet industry. The refined data contains 147 products and over 14,000 reviews observed weekly for 24 weeks starting from February 1, 2012. This allows us to construct a panel at the product-by-week level to empirically identify the value of displaying the VP badge in the online reviews on product sales and price. The data consists of three components: (a) the market dynamics of products, (b) product characteristics, and (c) consumer-generated product reviews. We summarize and briefly describe the variables in Appendix Table A1.

Table 1 reports our descriptive statistics. Our sample contains a total of 14,065 reviews with mean rating 3.76 (on a 5-point scale, 1 through 5 where 5 is the highest). About 60% are VP reviews and these have a slightly higher mean rating than the non-VP reviews (3.82 vs 3.67). VP and non-VP reviews are perceived almost equally helpful. The mean weekly percentage of helpful votes at 67.1% and 66.8%, respectively. On average the most recent review is 18 days (median at 8 days) ahead of the data collection date on each Wednesday. Given the shipping and handling time, the time lapse between order date and true review date could be at least two to three weeks. The average product price is about $400, and the mean sales rank is around 1,400.

4. Method

Amazon is a closed environment for consumers to make purchase decisions by examining the product specifics and reviews, and an open environment for pricing decisions which are determined by firms or the platform. Our primary interest is in the sales of the product. We use the following model to quantify the effect of VP reviews on purchase decisions:

$$y_{it} = \beta_1 r_{it} + w_{it}{}'\beta_2 + \psi_i + \pi_t + v_{it}. \qquad (1)$$

The outcome, y_{it}, is the logarithm of the sales rank of product i ($i = 1,2,\cdots,147$) at week t ($t = 1,2,\cdots,24$). Amazon does not disclose sales quantity but instead shows sales rank in the Tablets and Tablet PC's category on the product page. Sales rank is calculated based on the recent quantity sold in a given short time period with exponential decay in weight with respect to the time lapse to the current time (the exact formula is not disclosed and can only be approximated, [6, 11]). That said, sales rank is more a statistic of recent sales than the grand total cumulative sales since product launch on Amazon. Log sales rank is a well-accepted proxy for sales volume and has been used in previous literature [3, 6, 7, 17, 24], (see Appendix). As sales rank is inversely related to sales, we transform sales rank to make interpretation easier (see Appendix).

The other outcome variable that we examine is product price. Unlike sales which are determined by consumer choice, price results from managerial choices. Also, unlike the purchase/no purchase decision by consumers, Amazon is not a closed environment for pricing decisions -- this is determined by firms/platforms that compete in other marketplaces. If VP reviews do affect product sales, then this would give the firms or platforms additional pricing power to increase the selling price. A similar effect has been identified on eBay where sellers charge a price premium [31]. Hence, we use the same model in (1) to test the effect of VP reviews on product price. Our product price variable is the ratio of weekly selling price over the baseline price, where the baseline price is the listing price in the first week each product appears in our dataset. Thus, our price variable is a relative price – relative to the baseline listing price. We briefly describe our pricing results later and the analysis is shown in the Appendix.

The primary predictor, r_{it}, is the proportion of VP reviews (those with the VP badge) from the most recent 50 reviews of product i by week t. Amazon by default shows reviews in reverse chronological order with 10 reviews per page on the review pages and does not sort reviews by factors other than time of submission. The most recent 50 reviews to date are shown on the first 5 pages; for products with fewer than 50 reviews, the predictor is then the proportion of VP reviews out of all reviews. We also estimate the effects using the latest 20 reviews (latest reviews on the first 2 review pages) and the latest 100 reviews (latest reviews on the first 10 review pages) reviews to mimic situations when consumers are less or more patient, respectively. We hypothesize that a higher proportion of VP reviews is related to both higher log sales rank and higher relative price. Hence, we hypothesize that β_1 will be positive for both the sales and price equations. This coefficient estimates the incremental effect of VP reviews after controlling for other important characteristics.

There is a possible endogeneity in our model. The proportion of VP reviews is a subsample of orders during the recent time period. That is, these reviewers have purchased the product recently. This subsample and the sales rank, a measure based on sales in the most recent short period, should both be related to the entire recent demand for the focal product, which is an omitted variable. Therefore, we construct an instrumental variable (IV) to address the endogeneity of VP reviews. We use lagged variables as IV to address the endogeneity issues as adopted in Archak et al. [3] and Gu et al. [17]. We use the one-week (one-period) lagged total number of helpful votes on all reviews of the focal product, i.e. total helpful votes of product i by week $t-1$, as the IV for the proportion of VP reviews at week t. Helpful votes are voted by consumers who have read the reviews, so the total count of helpful votes is positively related to the number of consumers that have considered purchasing on Amazon, which is a measure of long-term aggregated number of consumers interested in the focal product. Thus, it is positively related to the actual aggregate demand for the focal product. Therefore, the IV is related to the endogenous variable, a subset of demand covering the relatively recent time period. This IV should also satisfy the exclusion criterion by being uncorrelated with the concurrent week demand shock, i.e. the error term, because the total count is a long-term relatively slow-moving aggregate [37]. In addition, we used one-week lagged total count. So it should be unrelated to the error term of the contemporary week. In the regression analysis, we have also tried alternative lagged total helpful votes including two-, three-, and four-week lags to empirically examine this assumption as there is no formal test for the exclusion assumption.

Our specification of (1) also includes a set of controls. First set contains product fixed effects, ψ_i, to account for product heterogeneity including product-specific media exposure and product life cycle.[7] The second is a week fixed effects, π_t, to account for common time trend.[8] The third is a vector of dynamic product-specific control variables, w_{it}, to control for characteristics of the product, the review, and the market. Specifically, w_{it} consists of the ratio of weekly selling price over the baseline price of the focal product, the average ratio of weekly selling price over the baseline price and the logarithm of average sales rank of competing products, the average rating of all reviews of the focal product by week *t*, the helpful votes of the most recent 50 reviews of the focal product by week *t*, the number of merchants selling the new focal product (and squared), and the lowest price for a new focal product. Competing products are those from other brands in the same market share cluster (high, medium, or low, see caption of appendix Figure A1). In our price equation the ratio of weekly selling price over the baseline price of the focal product becomes our outcome variable.

VP reviews come from reviewers that have purchased the focal products. These reviewers represent realized past demand whereas sales represent current demand. The most recent VP reviews are likely to be weeks prior to the sales at concurrent week t. Hence, we use a first-order autoregressive model, AR(1), to address the serial correlation. We also test the effects using standard errors one-way clustered on product to account for potential heteroskedasticity and serial correlation within panel.

[7] Product fixed effects are a series of dummies, one for each of the 147 products.
[8] Week fixed effects are a series of dummies, one for each of the 24 weeks.

5. Results

Table 2 shows the effect of VP reviews on sales. From columns 1 to 2, we add market characteristics into the regression. Column 3 reports the results using an IV with the same specification as in column 2 and is the most inclusive model with IV, and is our preferred working model; the significant effects are relatively consistent in magnitude across models. Table 2 reports the standard errors one-way clustered at product level. We also tested the effect under an AR(1) specification. Those standard errors are smaller (results not shown). Because one-way clustering assumes arbitrary autocorrelation within product, it is more conservative.

The proportion of VP reviews is significantly and positively associated with log sales rank, that is, the higher such proportion the higher log sales rank. The magnitude increases slightly with more control variables included in the regression. Such estimates are significant even without the use of IV. The estimated effect using IV becomes larger, which is common when comparing ordinary least squares (OLS) and two-stage least squares (2SLS) estimates, though the latter is marginally significant at 10% level. We have also used an IV constructed of total helpful votes in earlier weeks including two-, three-, and four-week lag. All results using the various IVs are qualitatively the same.

In Table A2 in the appendix, we present the results of the regression of endogenous variables on the instruments and other exogenous variables and fixed effects from the first-stage estimation. Here we consider a flexible specification of error terms by allowing heteroskedasticity and autocorrelations via one-way clustering on product. Table A2 shows that our proposed instrument is significantly and positively correlated with the corresponding endogenous variable. Furthermore, the first stage F-statistics are very close to, though slightly below, 10 which is the rule of thumb of not having a weak instrument. The first stage F-statistics are all above 10 when we use helpful votes with two-, three-, and four-week lag. This offers us assurance that we have a reasonable IV for our analyses.

The column 3 result shows that 10% additional reviews on the first 5 pages with VP (about half of the standard deviation; see Table 1 & 2) would increase the log sales rank by 0.241 ($= 2.410 \times 10\%$). Based on the estimated relationship between sales rank and the actual sales quantity from previous literature, this change corresponds to an increase in sales quantity of approximately 21.3% with 95% confidence interval at [-1.3%, 49.0%] (see Appendix). We have also tried an alternative predictor: average rating of the latest 50 VP reviews. The effect is not significant (results not shown). This suggests that effect on sales does not stem from what is said in the review but directly from the VP badge.

In the OLS results, review helpfulness is positively and significantly related to product sales. The most interesting insignificant result is the effect of focal product mean rating. The coefficient estimate is positive, but in the presence of the proportion of VP reviews, it is insignificant. This suggests that the proportion of VP reviews matter instead of the mean review rating.

The price of the focal product is negatively related to the focal product sales, and that of competitors is positively related. Both associations are significant and consistent with microeconomics. Own price elasticity is negative and cross-price elasticity is positive: lower focal price and higher competitor price are related to higher sales of the focal product. Although not significant, coefficient estimates of competitor sales is consistent with prior research such that lower competitor sales are related to higher focal product log sale rank. There could be collinearity between prices driven by competition and common technological obsolescence, but this may only serve to inflate the standard errors and does not bias the estimates.

In Table 3 we report the results using alternative model specifications. All results are obtained using 2SLS with total helpful votes on all reviews in the previous week as our IV. The results of the preferred working model (Table 2, column 3) are also provided (Table 3 column 1) for comparison. In column 2, we use a one-week lagged predictor, i.e. the proportion of VP reviews in the latest 50 reviews in one-week lag. In this specification, the IV is two-week lagged total helpful votes. In column 3, we replace the week fixed effects with a common quadratic trend. The estimates change only minimally. The estimates of all covariates are consistent across our specifications. We also consider the scenarios that consumers read the most recent 20 reviews (on the first 2 pages, i.e., less patient) or read 100 reviews (on the first 10 pages, i.e., more patient). In both the alternative scenarios the effects of the proportion of VP reviews are positive and significant (not shown) and the coefficient estimates have similar magnitudes to those in column 1.

The results on relative product price are reported in the Appendix. In summary, the OLS results show that the effect of the proportion of VP reviews are qualitatively similar to those on log sales rank, yet with smaller magnitudes and lower significance levels. The estimated effect remains positive but becomes insignificant using 2SLS, suggesting potential endogeneity between price and actual purchases – endogeneity that is not surprising.

6. Discussion and Conclusion

Our main objective is to investigate the effects of displaying purchase verification in online reviews on product sales and selling price. We have shown that the proportion of VP reviews is positively associated with fluctuations in sales after controlling for product heterogeneity, time trend, and a rich set of dynamic covariates. We have also shown that with VP reviews included in the specification, the mean review rating is uncorrelated to sales. Consequently, we find that a specific volume of the VP reviews within a larger set of reviews bears a greater explanatory power than the mean review rating. Rating of VP reviews, on the other hand, does not affect the product sales. It further corroborates our hypothesis that the effect of VP reviews stem from the revealed preference of reviewers.[9] Our preferred model and various alternative specifications, including a specification using IV, yield consistent results.

[9] If the effect comes from other angles, such as reliability of reviews, then we should expect a significant positive effect of VP review ratings.

Our results on product price are revealing but are not conclusive. The OLS regression shows a marginally significant effect of VP reviews. However, the effect becomes insignificant when our IV is used. In addition, the explanatory power of our model on price is lower than that on sales (R^2 between 0.74-0.76 versus approximately 0.92). Such results are not that surprising as pricing is the firm's/platform's decision—not the consumers' decisions as would be the case for a purchase. Unlike consumers, firms/platforms have the capability to track reviews over time and make decisions based on this past information. The lagged predictor model (results not shown) has larger but insignificant effects and higher R^2 than the concurrent week predictor model (Table A3 column 3), suggesting that it takes time for the firm/platform to react to the observed effect on sales. The lack of strong evidence of the effect of VP reviews on price warrants future research.

Our results show that the proportion of VP reviews positively and simultaneously impacts sales and price. The relatively larger influence on sales has implications for firms, platforms, and consumers as it provides a beneficial solution for all parties. By emphasizing VP reviews, firms would enjoy higher revenue through increased demand and possibly higher prices, and platforms would be more attractive to firms as they would earn more revenue. With a larger collection of products from a wider range of firms, more consumers would be attracted to the platform to seek genuine and reliable opinions from consumers whose purchases are verified.

6.1. Limitations

We have shown a significant relationship between sales and price with the proportion of VP reviews, but not the mechanisms through which they are related. We proposed an explanation following the theory of revealed preference that the VP reveals consumers' true utility maximization choices among alternatives, establishing their preferences. This makes a consumer's VP review more authentic in that their preference has been revealed by their choice and their subsequent experience with the focal product. Clarifying this relationship warrants further research.

We also recognize that purchase verification is unlikely to be a straightforward solution to review manipulation. For Amazon, the VP badge is only an endorsement from Amazon confirming that the reviewer did in fact buy the product on Amazon – indeed the VP review is related to both the focal product and Amazon. The VP badge also does not guarantee that the seller did not hire the buyer to purchase the product and leave a spuriously positive message. In recent years, Amazon has sued several sellers for buying non-authentic reviews.[10] As a separate but related issue for consideration, Amazon has recently updated their custom review system to prohibit incentivized reviews unless they are facilitated through the Vine program whereby Amazon, not the vendor or seller, invites reviews.[11] Nevertheless, Mayzlin et al. [29] show that purchase verification in the hotel booking industry is related to fewer non-authentic reviews.

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[10] https://techcrunch.com/2016/06/01/amazon-sues-sellers-for-buying-fake-reviews (accessed November 8, 2019).
[11] https://www.amazon.com/p/feature/abpto3jt7fhb5oc?tag=skim1x174507-20 (accessed November 8, 2019).

Figure 1. Badge of verified purchase on Amazon.com.

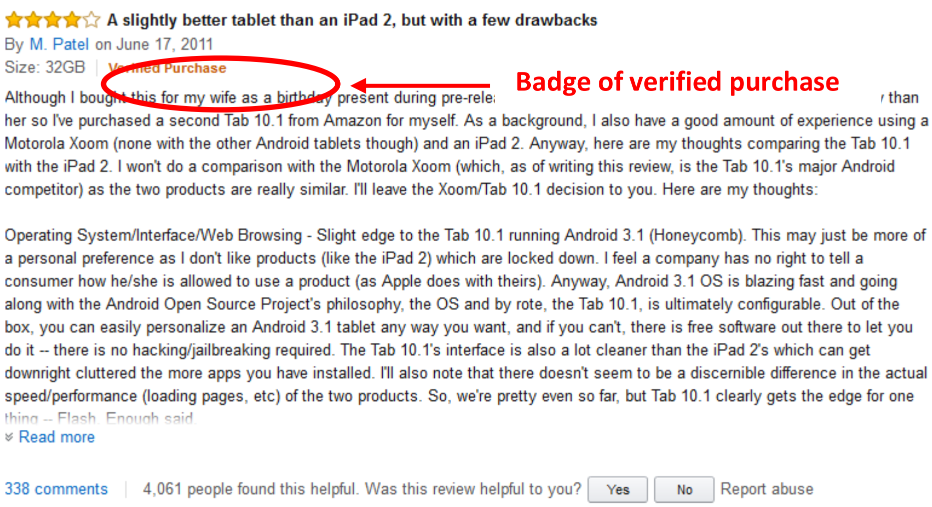

Table 1. Descriptive statistics.

Variables	N	Mean	SD
Review characteristics			
With verified purchase badge (yes=1, no=0)	14,065	0.62	0.49
Rating	14,065	3.76	1.45
Verified purchase	8,665	3.82	1.43
Non-Verified purchase	5,400	3.67	1.48
Weekly percentage of helpful votes (%)	238,707	66.98	35.53
Verified purchase	137,628	67.13	36.74
Non-verified purchase	101,079	66.77	33.81
Product (N = 147) x Week (N = 24) panel			
Sales rank	3,144	1,430	5,591

Selling price ($)	2,787	401.10	239.95
Baseline listing price ($)	147	461.16	237.63
Number of reviews, first 5 pages (counts)	3,100	32.49	18.51
Proportion of VP reviews, first 5 pages	3,100	0.61	0.23
Mean helpful votes, first 5 pages (counts)	3,100	6.24	20.68

Table 2. Effect of VP reviews on sales. Columns 1 and 2 report the OLS results. Column 3 reports the 2SLS results using total helpful votes on all reviews in the previous week as the instrumental variable. Standard errors are one-way clustered on product and reported in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.1 levels, respectively.

	OLS		2SLS w/IV
Variables	(1)	(2)	(3)
Proportion of VP reviews,	**0.608*** **	**0.622*** **	**2.410***
latest (50 reviews)	**(0.191)**	**(0.198)**	**(1.315)**
Ratio of weekly selling price over	-0.028***	-0.023***	-0.024***
baseline listing price, focal product	(0.006)	(0.007)	(0.007)
Mean ratio of weekly selling price over	0.016***	0.017***	0.013**
baseline listing price, competitors	(0.005)	(0.005)	(0.006)
Mean competitor sales rank, in logs	-0.050	-0.044	-0.025
	(0.032)	(0.032)	(0.031)
Mean rating	0.131	0.143	0.219
	(0.121)	(0.134)	(0.161)
Mean helpful votes (latest 50 reviews)	0.004***	0.004***	-

	(0.001)	(0.001)	-
Total number of merchants	-	0.010**	0.009*
selling new products	-	(0.005)	(0.005)
Total number of merchants	-	-0.00005	-0.00003
selling new products, squared	-	(0.00003)	(0.00003)
Lowest new product price	-	-0.002***	-0.002**
quoted by merchants ($)	-	(0.001)	(0.001)
First stage F-statistic	-	-	9.65
Observations	2,680	2,452	2,375
R-squared	0.917	0.914	-
Mean value of sales rank, in logs	6.38	6.45	6.44

Table 3. Effects of VP reviews on sales, robustness tests. Column 1 is the preferred working model (Table 2 column 3). Column 2 uses one-week lag proportion of VP reviews. Column 3 replaces the week fixed effect in the preferred model (column 1) with a quadratic trend. Also see notes in Table 2. ***, **, and * denote significance at the 0.01, 0.05, and 0.1 levels, respectively. Also see notes in Table 2.

	Preferred model	One-week lag	Quadratic trend
Variables	(1)	(2)	(3)
Proportion of VP reviews	**2.410***	**-**	**2.448***
	(1.315)	**-**	**(1.313)**
Proportion of VP reviews,	**-**	**2.867*****	**-**
one-week lag	**-**	**(1.102)**	**-**

Ratio of weekly selling price over	-0.024***	-0.023***	-0.024***
baseline listing price, focal product	(0.007)	(0.007)	(0.007)
Mean ratio of weekly selling price over	0.013**	0.013**	0.012**
baseline listing price, competitors	(0.006)	(0.006)	(0.005)
Mean competitor sales rank, in logs	-0.025	-0.020	-0.034
	(0.031)	(0.030)	(0.021)
Mean rating	0.219	0.245	0.213
	(0.161)	(0.183)	(0.162)
Total number of merchants	0.009*	0.005	0.008*
selling new products	(0.005)	(0.006)	(0.005)
Total number of merchants	-0.00003	0.00004	-0.00003
selling new products, squared	(0.00003)	(0.00006)	(0.00003)
Lowest new product price	-0.002**	-0.002***	-0.002**
quoted by merchants ($)	(0.001)	(0.001)	(0.001)
First stage F-statistic	9.65	9.10	9.86
Observations	2,375	2,263	2,375
Mean value of sales rank, in logs	6.44	6.44	6.44

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APPENDIX

A. Sales rank and log sales rank

Instead of disclosing the actual quantity sold, Amazon only shows the rank of sales within a specific category on the product page. Appendix Figure A2 gives an example of how sales rank is displayed on the product page. Note that in the original scale, the smaller the rank, the higher sales (i.e. quantity sold) of the product. Hence, using the raw log sales rank, we would get a negative estimate of β_1 in equation (1) if more reviews with the verified purchase (VP) badge are related to larger sales quantity. Therefore, we take a linear transformation of the log sales rank to make the interpretation easier. Using the transformed sales rank, if more reviews with the VP badge are associated with higher sales, then the coefficient β_1 will be positive. For the sake of brevity and of reference to the original measure, we still call this outcome the log of sales rank, or simply sales rank.

B. Relationship between sales rank and quantity sold

Previous studies [1, 2, 6] have identified a Pareto relationship between Amazon sales rank and sales quantity:

$$\ln(Sales) = \alpha + \beta \ln\,(Sales\ rank), \qquad \text{(A.1)}$$

with α and β being industry-specific parameters. Note that the coefficient β is positive due to the linear transformation on log sales rank. Now the interpretation is that the higher the sales rank, the higher the sales volume. For example, β is between 0.9 and 1.3 for books [1], $\beta = 0.828$ for software [2], and $\beta = 1.70$ for DVDs [6]. We adopt the same rule and in the back of the envelope calculations take the value of $\beta = 0.8$ that is close to the β of software, the closest category to tablets. Using the estimated effect in column 3, the increase in sales quantity is then $\Delta \log(Sales) = 0.8 \times \Delta\log\,(Sales\ rank)$. Thus, $\Delta Sales = \exp(0.8 \times 2.410) - 100\% = 21.3\%$. The 95% confidence interval is estimated similarly at [-1.3%, 49.0%]. To account for the uncertainty of β, we also pick two “extreme” values at 0.6 and 1.2, which corresponds to a 15.6% to 33.5% increase in sales. Increases at 5% and 20% are related to 10.1% and 47.0% increases in the sales quantity, respectively.

C. Results on Selling Prices

We also use our model from equation (1) in the main text to examine the effects of VP reviews on the selling price. The outcome is the ratio of weekly selling price over the baseline listing price. This is a normalized variable so that all products are placed on the same threshold. For example, a change of $20 for a $200 tablet is equivalent to a $50 change for a $500 tablet since price changes are in percentages. This variable is also consistent with log sales rank, our normalized sales variable. The covariates are the same as in the sales equation except without ratio of weekly selling price over baseline listing price of the focal product since it is now the dependent variable. The results are reported in Table A3. Column 1 reports the OLS results. The proportion of VP reviews is significantly and positively associated with the selling price. The estimate indicates that a 10% additional increase in VP reviews is related to a 0.46% ($= 4.571 \times 10\%$) increase with respect to the baseline listing price. The average baseline listing price is $461 (see Table 1). Therefore, the increase is equivalent to $2.11. This is about 0.53% of the average selling price in the study period. However, when our IV is used, the effect on price (column 2) becomes insignificant although the magnitude is larger.

Focal product price is not correlated with competitor price though the coefficient is positive. This might be due to the price matching between main competitors, in particular between Apple and Samsung. We find a relatively high correlation at 0.49 between the average Apple and Samsung price. If we restrict the sample period to only after iPad third generation was launched, then this correlation increases dramatically to 0.89. Our market characteristics also include the lowest price for the new focal product which could be the relevant competition when it comes to price.

Note that sales and price are two outcomes of the same product. It is very likely that the error terms in the two equations are correlated. Plus, they form a triangular system as defined in Lahiri and Schmidt

[4]. Therefore, as an additional robustness check (results are available from the authors) we apply the seemingly unrelated regression (SUR) approach to fit the two equations simultaneously and obtain the consistent estimates. The same strategy is also adopted in Godes and Mayzline [3]. Note that IV is not used in this robustness test. As the two equations are jointly estimated, the final samples used in the regressions are those with non-missing values for all the variables involved. In our SUR estimation we use the same 2452 samples as were used for the sales equation (Table 2 Column 2). The point estimates of the log sales rank equation are identical to those in Table 2. The price equation estimations are slightly different from those in Table A3 due to different sample sizes (results are available from the authors). Because the SUR approach does not allow clustering, the standard errors are consistently smaller than the clustered ones in Tables 2 and A2.

Table A1. List of variables used in the study.

Variable Name[a]	**Description**
Part A: Market dynamics of products	
Item_ID	Amazon Standard Identification Number (ASIN): Amazon assigns a unique identification number to each product
Brand	Brand name of the product
Amazon_price	Current selling price of the product
List_price	Retail price suggested by the manufacturer
Lowest_new_price	Lowest new product price quoted by merchants
Total_new	Total number of merchants selling new products
Num_reviews	Number of reviews submitted up to the collection day
Sales_rank	Sales rank in the tablets and tablet PCs category
Part B: Product characteristic information	
Item_ID	Amazon Standard Identification Number (ASIN) of the product

Date_first_available	Release date of the product
Part C: Consumer-Generated Product Reviews of Tablet Computers	
Review_ID	Unique identification number for each review
Item_ID	Amazon Standard Identification Number (ASIN)
Review_date	Date the review was submitted
Rating	Numerical rating of the review (1–5 stars)
Verified_purchase	Binary variable that indicates whether the product purchase was made on Amazon
Total_votes (24 weeks)[b]	Total number of reviewers who voted
Helpful_votes (24 weeks)[b]	Number of reviewers who voted "Yes" (vs. on "Was this review helpful to you?"

Table A2. Effects of VP reviews on sales, robustness tests, first stage estimates. This table reports the first stage regression estimates of 2SLS regressions reported in Table 2. The instrumental variable in columns 1 and 3 are one-week lagged cumulative total helpful votes of all reviews. The instrumental variable in column 2 is two-week lagged cumulative total helpful votes of all reviews. Also see notes in Table 2.

	Preferred model	One-week lag VP reviews	Quadratic Trend
Variables	(1)	(2)	(3)
Cumulative total helpful votes,	0.0329***	-	0.0330***
one-week lag	(0.0106)	-	(0.0105)
Cumulative total helpful votes,	-	0.0291***	-

two-week lag	-	(0.0096)	-
Ratio of weekly selling price over	0.0007*	0.0004	0.0006**
baseline listing price, focal product	(0.0004)	(0.0005)	(0.0003)
Mean ratio of weekly selling price over	0.0026***	0.0039***	0.0026***
baseline listing price, competitors	(0.0009)	(0.0011)	(0.0009)
Mean competitor sales rank, in logs	-0.0065*	-0.0018	-0.0043
	(0.0037)	(0.0051)	(0.0035)
Mean rating	-0.0622	-0.0583	-0.0625
	(0.0416)	(0.0438)	(0.0417)
Total number of merchants	-0.0018	-0.0019	-0.0019*
selling new products	(0.0011)	(0.0014)	(0.0010)
Total number of merchants	0.0000	0.0000	0.0000
selling new products, squared	(0.0000)	(0.0000)	(0.0000)
Lowest new product price	-0.0002	-0.0001	-0.0002*
quoted by merchants ($)	(0.0001)	(0.0001)	(0.0001)
First stage F-statistic	9.65	9.10	9.86
Observations	2,375	2,263	2,375
R-squared	0.900	0.867	0.910

Table A3. Effect of verified purchase (VP) reviews on price. Column 1 reports the OLS results. Column 2 reports the 2SLS results using total helpful votes on all reviews in the previous week as IV. Standard errors are one-way clustered on product. ***, **, and * denote significance at the 0.01, 0.05, and 0.1 levels, respectively.

	OLS	2SLS w/ IV
Variables	(1)	(2)
Proportion of VP reviews,	**4.571***	**6.329**
latest 50 reviews	**(2.637)**	**(10.490)**
Mean ratio of weekly selling price over	0.032	0.038
baseline listing price, competitors	(0.069)	(0.066)
Mean competitor sales rank, in logs	-0.109	0.010
	(0.485)	(0.441)
Mean rating	-0.498	-0.288
	(0.945)	(1.062)
Mean helpful votes, first 5 pages	0.018**	-
	(0.007)	-
Total number of merchants	-0.120**	-0.099**
selling new products	(0.051)	(0.046)
Total number of merchants	0.0005*	0.0004
selling new products, squared	(0.0003)	(0.0003)
Lowest new product price	0.105***	0.103***
quoted by merchants ($)	(0.012)	(0.012)
First stage F-statistic	-	9.69
Observations	2,474	2,397
R-squared	0.739	0.754

Mean value of selling price ($)	414.52	415.51

Figure A1. Global tablet market share held by tablet vendors from Q2 2011 to Q1 2013. The "Other" group contains the category of "others" of the original report and all brands excluding 1) Apple, Samsung (high market share group), 2) Acer, Asus, and Lenovo (medium market share group), 3) Microsoft, Barnes & Noble, RCA, and LG (brands not included in the original data). Our sample period mainly spans the first two quarters of 2012 (indicated by the red rectangle). Source: IDC 2016 [5].

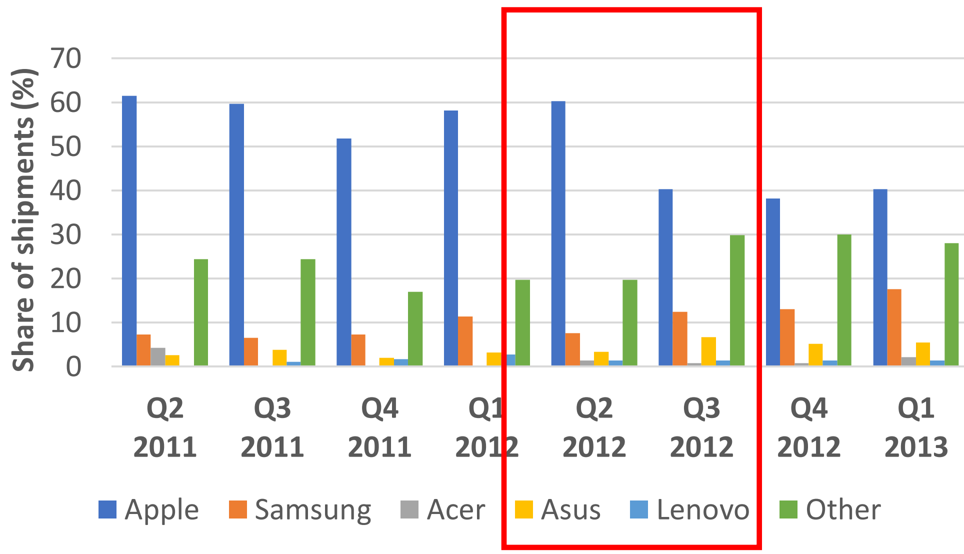

Figure A2. Sales rank on product page. Note that this screenshot below is only for illustration purpose as the data was collected in 2012 and the screenshot was taken in 2017. The list of categories have been updated during that period. The category was Tablet and Tablet PC when the data was actually collected.

ASIN	B00OTWQIZG
Customer Reviews	5,806 customer reviews 4.7 out of 5 stars
Best Sellers Rank	#451 in Computers & Accessories (See top 100) #99 in Computers & Accessories > Tablets
Shipping Weight	1.9 pounds (View shipping rates and policies)
Domestic Shipping	Item can be shipped within U.S.
International Shipping	This item is not eligible for international shipping. Learn More
Date First Available	October 16, 2014

APPENDIX REFERENCES

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