Caveat Emptor: Differences in Online Reputation Mechanisms

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Abstract

Using a unique dataset from a specialty online retailer, we are able to compare the effectiveness the of Amazon and eBay online reputation mechanisms. We develop a structural model of online order generation process, feedback generation process and price formation process. Results from our structural model suggest significant differences on how feedback affects total sales and how different types of order processing errors and consumer returns of ordered products influence consumers proclivity of provide feedback. We find feedback affects sales on the Amazon platform but not on the eBay platform. Products returns lead to significantly higher numbers of negative feedback, but processing errors at eBay perversely increase the number of positive feedback. Structural models suggest that the eBay feedback mechanism is neither effective nor is the process is intuitively interpretable. We then conduct an exploratory analysis to determine the causes for the differences between these two platforms, and conclude that the majority of the difference is due to the reciprocity effect.

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Introduction

Business-to-consumer (B2C) e-commerce in the United States exceeded $55 billion in 2004 and is growing at an average rate of 26% per year (Department of Commerce, 2005). Online marketplaces such as eBay, which foster transactions from one consumer to another consumer (C2C), continue to grow at an even faster pace: eBay alone processed 1.4 Billion transactions in 2004, which accounted for $34.2 billion changing hands and earning eBay $3.27 billion in commissions, representing approximately 45% annual growth (eBay 2005).

While all purchases contain some risk, the level of risk is much higher in the online context, in which the goods cannot be physically inspected and payments are not made at the site of the transaction. In such markets, the information asymmetry is particularly intense, in that the seller knows much more about the quality of the goods and his intent to fulfill the transaction than does the buyer. The seller would like to be able to commit to behave in a trustworthy manner and thereby maximize the buyer's willingness to pay, but, having no credible or cost-effective way to do so in the online context, the seller suffers the consequences of the resulting moral hazard. If these problems are severe enough, total market failure can ensue as only "lemons" (low quality goods/sellers) are available.

In order to mitigate the buyer's perception of the risks of buying online, retailers such as Amazon.com or Priceline.com have invested heavily in building their reputations for safe, secure, and predictable transactions. Meanwhile, electronic marketplaces such as eBay, Yahoo, and Amazon have emerged to facilitate transactions among independent buyers and sellers online; however, these marketplace providers cannot directly guarantee the trustworthiness of the participants in their markets. In order to overcome the information asymmetry and moral hazard problems, these marketplaces use a variety of "reputation mechanisms" to allow buyers and sellers to leave publicly visible feedback on each other's performance in transactions. For example, eBay allows each participant to leave feedback for the other party in a transaction that is either positive (+1), neutral (0), or negative (-1). The individual feedback items are aggregated into an index of the past behaviour of market participants, forming, in effect, an online "brand" for each participant. An eBay "score" is simply the sum of feedback received from unique users.

Despite the billions of dollars changing hands in these online marketplaces, surprisingly little is known about the effectiveness of online reputation mechanisms in countering the problems described above; indeed, the design of reputation mechanisms was highlighted in a recent survey of online auction research as the most important research question (Bajari and Hortaçsu, 2004). Although the rapid growth of online marketplaces such as eBay suggests that these mechanisms must "work" as there does not appear to be a strong case of market failure. However, online auctions have consistently been the most common type of internet fraud reported to the National Consumer League, accounting for more complaints than all other categories of internet fraud combined (National White Collar Crime Center, 2005).

Our research addresses the use of online reputation to overcome the information asymmetry and moral hazard problems using a unique dataset provided by a specialty online marketplace. Using these data, we compare of the most popular online reputation mechanisms (i.e., the one-way rating system of Amazon versus the two-way rating used on eBay) in terms of their ability to provide an unbiased signal of trustworthiness. We find a major difference between the two mechanisms, with negative feedback being approximately three times more common under the Amazon system. Since earlier research has consistently identified the two-way structure of eBay as introducing a positive bias in the reputation mechanism, we conclude that Amazon's system likely provides a more accurate signal of participant trustworthiness.

Using these data, we also assess of the impact of reputation and feedback on sales and prices under these two mechanisms using while accounting for the underlying sources of feedback using a structural model.

The remainder of the paper is structured as follows. In the next section, we review the existing research relating online reputation mechanisms and derive propositions relating to the differences between the eBay and Amazon mechanisms. We then describe the characteristics of data and derive our analytical structural model. We estimate this model and present our results, and conclude with a discussion of these results and proposals for future research.

This study makes timely and important empirical contributions, as it is one of the first if not the first to compare reputation mechanisms across two online retail marketplaces. It is also one of the first to examine implications of the choices made in the design dimensions of reputation mechanisms.

Reputation Mechanisms in Online Marketplaces

In order to mitigate the transaction risks in electronic marketplaces, providers have devised mechanisms like escrow, secured online payment (e.g., PayPal, BidPay), and user feedback and reputation mechanisms. Of these approaches, reputation and feedback play a number of crucial roles: building trust between traders, helping buyers and sellers generate goodwill and any associated price premium, and helping to evolve online trading norms of behaviour. As a result, reputation mechanisms help to avoid market failure due to adverse selection as well as moral hazard problems at online marketplaces (Cabral and Hortatcsu, 2004). Unlike other mechanisms, user feedback is voluntary and is usually provided by buyers and sellers after the trades are complete with minimal intervention of the market facilitator. As a result, current feedback and ratings have the potential to affect both buyers and sellers in all of their future transactions.

The purpose of this research is to empirically explore the role of feedback and ratings in online trading, which we operationalize in the context of new and refurbished consumer electronics. Outcomes of the research will provide insights into the effectiveness of feedback and ratings in avoiding adverse selections and moral hazard problems in online marketplaces. Electronics, along with books, CD's, and DVD's, are among the leading category of goods purchased over the Internet, and thus provide a representative perspective from which to study online purchase behaviour. Refurbished devices have the added advantage of providing more variability in quality and value than do new items, which makes risk and therefore reputation even more salient.

We utilize the consumer electronics context because a fruitful collaboration has already established with ABC Electronics, an internet-only marketplace for consumer electronics products located in Southern California.[1] ABCE has been operating since the mid-1990s and maintains its own website at a marketplace under which individual sellers can list their own inventories; in addition, ABCE re-lists its sellers' inventories under the ABC Electronics ID on two other sites, Amazon.com and Half.com (a subsidiary of eBay). In 2004, ABCE listed more than 2500 sellers as customers, and ABCE's revenues were more than US$ 10 million. ABCE competes with other online marketplaces, as well as electronics retailers, both online and offline. As part of an ongoing collaborative project ABCE has provided access to proprietary transaction data, which we combine with publicly available feedback from online marketplaces.

[1] Because ABC Electronics is a privately held corporation, a number of company details – including the name – have been disguised in order to preserve the confidentiality of proprietary financial information and internal operational details.

Based on a recent literature review, fourteen papers have explored the role of feedback mechanisms in online marketplaces from an empirical perspective (Bajari and Hortatcsu, 2004).[4] Most of these studies were based on publicly available feedback data "scraped" from eBay's website, although some utilized field experiments at eBay. Excepting Cabral and Hortatcsu (2004), all of the studies use reduced form econometric methodology to test the impact of online feedback on auction outcomes (number of bids, likelihood of sale, and prices).

The results of these studies are mixed. Some studies find a significant relationship between positive feedback and closing price (Houser and Wooders, 2000; Lucking-Reiley, Bryan, Prasad and Reeves, 2000; McDonald and Slawson, 2000; Melnik and Alm, 2000) or the number of bids received (McDonald and Slawson, 2000). Some studies also find a strong impact of negative feedback in lowering the closing price (Lucking-Reiley et al, 2000), whereas most do not find any effect of negative feedback. Others find that positive feedback increases the probability of a sale, but has no impact on closing price (Resnick and Zeckhauser, 2001). The existing studies suffer from a number shortcomings.

First, all the studies we reviewed only use data from eBay. However, eBay uses a specific feedback mechanism that is different from mechanisms used at other sites, including Amazon and Yahoo. The eBay mechanism is "two-way" in that it allows both buyers to rate sellers and sellers to rate buyers, whereas Amazon is "one-way" in that only buyers can rate sellers. As a result, incentives to leave feedback are different at these two sites. Cabral and Hortatcsu finds

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[4] There also exists research that explores reputation mechanisms in terms of their algorithmic components, largely from the perspective of computer science. We do not explore this research in this study, but an online bibliography is available at: http://databases.si.umich.edu/reputations/bib/bib.html

that a buyer leaving negative feedback has a 40% probability of also receiving negative feedback by the seller; this tit-for-tat strategy used by sellers dramatically undermines the incentive of buyers to leave negative feedback. There are other differences in the rating mechanisms across different sites, such as the rating scales used (1-5 vs. -1, 0, 1). Confining research to only one reputation mechanism creates a major limitation in that the impacts of the various dimensions of reputation mechanisms cannot be explored. Our discussions with ABCE management indicate that significant differences in feedback behaviour exist across the eBay and Amazon sites; our research will address this blind spot by comparing the eBay and Amazon reputation mechanisms.

Second, the existing studies explored the role of feedback only in the context of online auctions. However, we know that consumer behaviour tends to be very different in the traditional fixed-price retail context versus auctions. For example, Ku, Malhotra, and Murninghan (2003) suggest that consumers' valuation of products can be influenced by the online auction process, particularly the timing and increment of bids from other sellers. Confining research solely to the auction context again creates a shortfall of knowledge, especially considering that auctions account for less than 30% of total B2C e-commerce sales (Department of Commerce, 2005). Our research will address this shortfall by specifically examining the impact of reputation mechanisms in the retail context.

Third, the extant literature highlights a disproportionate quantity of positive versus negative feedback on eBay. This unrealistic bias toward positive feedback raises concern as to the accuracy and effectiveness of eBay feedback mechanism. For example, Resnick and Zeckhauser (2001) found that only 0.6% of the feedback provided by buyers was negative; similarly, Bajari and Hortatscu (2004) find only 0.43% negative feedback. It has been hypothesized that the bias toward positive feedback is a result of eBay's two-way rating mechanism. Likewise, the existing literature also finds an extremely high rate of feedback on eBay, much higher than would be expected in a retail context. We hypothesize that a number of the "general" findings regarding online reputation mechanisms that have emerged are, in fact, idiosyncratic to the eBay mechanism and that our research will begin exploration of the impact of different mechanism designs.

Fourth, the research published to date is strikingly homogeneous in a number of ways, including: (i) almost all the studies deal with very low-priced products, creating an environment in which financial risk is low and therefore reputation mechanisms are less important, and (ii) all of the studies examined a single reputation mechanism, and therefore were not able to examine the differences across the different dimensions of reputation design. We aim to increase the breadth of the literature by studying higher-priced goods that make financial risk more important, as well as comparing reputation mechanisms that vary on two dimensions rating scale and direction of feedback..

Data

Data for our research comes from two sources. Feedback data were captured by the existing reputation mechanisms of eBay.com (on the Half.com website) and Amazon.com. These feedback data are publicly available on the on the Half.com and Amazon.com websites, and were "harvested" over time using web robots. Currently, the union of these datasets spans November 2003 – October 2004.

A description of the feedback for all sellers on the two platforms is presented in Table 1. Note that we have collapsed the 5-point Amazon rating scale down to the 3-point rating scale of eBay. Here, we simply lumped an Amazon score of 4 or 5 into "positive" feedback, an Amazon score of 1 or 2 into "negative" feedback, and an Amazon score of 3 into "neutral" feedback.

This is the description that Amazon publishes and uses on its own website to provide an aggregation of feedback for sellers over time. In total, 218,445 pieces of unique feedback were captured.

These feedback data are matched with proprietary weekly unit price, unit sales, transaction status codes and product return data from ABCE. To match weekly sales and unit price data from ABCE, harvested feedback data is aggregated at the weekly level. This provides us with 105 weekly data points across the two platforms (with 62 data points for Half and 43 data points for Amazon). As a result of this transformation each data point in our panel implies a specific week and platform.

Table 1 provides descriptive statistics of some of the critical variables of our structural model analysis, and Figures 1, 2 and 3 provide unit price, unit sales, and feedback by platform. Note that unit price and sales in Amazon platform is significantly larger than Half platform. These numbers reflect the fact that for ABCE the Amazon retail platform is dominates eBay's retail platform in terms of transactions. In Figure 3, we present plots of three types of feedback over time. The overwhelming proportion of feedback received under both reputation mechanisms is positive. On Half, the number of negative and neutral feedback is approximately equal, while on Amazon there is more negative feedback than neutral feedback.

The Model

The primary goal of this study is to document the impact of the differences in the design of the eBay and Amazon reputation mechanisms, arguably the two most "popular" mechanisms in terms of usage on the Internet.[5] For this purpose we will first develop a structural model by taking into account how reputation affects sales, how transaction processes generates feedback

[5] Yahoo Auctions uses a three-point, two-way reputation mechanism that is very close in design to eBay's system.

and how prices are formed. The path diagram in Figure 1 describes our approach to this structural model. Our structural model takes into account the decision processes of both consumers (or "buyers") and sellers.

The consumer decision process: Following the literature on the effects of reputation mechanism on auction markets, we postulate that a consumer's decisions to purchase is influenced by the existing feedback that they observe at the time of purchase. We also postulate that consumers are motivated to leave feedback at the website for one of three reasons: altruistic information sharing, revenge, or self-interest. In transactions that are conducted to the satisfaction of the buyer, the leaving of feedback could either reflect a selfless desire to tell others about the good service they received, or, in a two-way reputation mechanism, a self-interested manoeuvre designed to elicit positive feedback in return and thereby build the buyer's own reputation mechanism. We do note that a poor transaction, either as a result of errors in the fulfillment process or due to dissatisfaction with the products received, may motivate buyers to leave negative feedback as a "punishment." We therefore hypothesise that consumer satisfaction will be sensitive to price paid for a product, with higher prices leading to a higher probability of leaving feedback. And at the aggregate level, we expect a strong correlation between feedback and unit price paid by the consumers.

Seller Decision Process: The primary role of seller in our model is to strategically set prices after taking into account its own pricing history, customer feedback history, fluctuation in inventories from the variability in customer returns of already sold books. It is probable that the seller also use customer relationship management techniques to control for any negative effects from annoyed and dissatisfied consumers due to poor service or lower than expected product quality.

We express these structural relationships through a system of three equations:

$$Sales = f\left(Market\,binaries, \Pr ice, Lagged\ Feedback\right)$$
$$Feedback = f\left(Market\,binaries, Lagged \Pr ice, Errors\ and\ \mathrm{Re}\,turns\right)$$
$$\Pr ice = f\left(Market\,binaries, Lagged \Pr ice, Lagged\ Feedback\right)$$

As this is the first study to explore structural relationships between sales, feedback, price, and different kinds of system errors and returns from dissatisfied consumers, we remain agnostic regarding specific functional forms. Our choice of functional forms is also influenced by the level of data aggregation, institutional peculiarities and data artefacts.

So, based on our preliminary data analysis and regression diagnostics we specify the following parsimonious functional form of the structural model:

$$\begin{aligned} V_{it} &= bin_{eV} + bin_{AV} + bin_{sV} + \upsilon_p p_{it} + \upsilon_{p2} p_{it}^2 + \upsilon_f PPF_{it} \\ PPF_{it} &= bin_{ePPF} + bin_{APPF} + bin_{sPPF} + \pi_{wp} wp_{it} + \pi_{SER} SER_{it} \\ p_{it} &= bin_{ep} + bin_{Ap} + bin_{sp} + \varphi_p p_{it-1} + \varphi_R RET_{it} \end{aligned} \tag{1.1}$$

Here:

V_{it}: Unit sales in week t on platform i (i.e., either eBay or else Amazon), Measured in \$ thousand b_{eV}, b_{AV} *: Platform specific binaries in sales equation*

b_{ePPF}, b_{APPF} *: Platform specific binaries in cumulative percentage positive feedback equation*

b_{ep}, b_{Ap} *: Platform specific binaries in price equation*

p_{it} *: average weekly unit price paid by consumers on platform i*

b_{sV}, b_{sPPF}, b_{sp} *: Indicator variable for peak holiday buying season*

$PPF_{it}: \sum_{t=0}^{t-1} \frac{positive_{it}}{positive_{it} + neutral_{it} + negative_{it}}$ *for each i.*

$RET_{it}: \sum_{t=0}^{t-1} \frac{System\,errors_{it} + \mathrm{Re}\,turns_{it}}{V_{it}}$ *for each i.*

As mentioned before, most studies have used reduced-form econometric models to explore the linkages between market outcomes and feedback and ratings. However, our access to "back office" data permits us to estimate a full structural model where we not only take into account how demand and price is effected by feedback but also account for the determinants of feedback. In this model, the demand on ABCE through Amazon and Half is a function of the feedback to date received by ABCE, the price of the goods, and controls for the platform and the holiday buying season. We use the same cumulative measure of feedback across the two platforms, percentage of positive feedback. Not only is this measure normalized across the number of feedback received across the two platforms, but it is also similar to the cumulative measures presented by the reputation mechanisms on the two sites. Half explicitly presents a (biased) version of % positive feedback (omitting neutral feedback from the denominator), and Amazon presents an average feedback score (out of 5.0) based on all feedback received to date. Our preliminary data analysis also suggests high degree of correlation (0.9) between the three types of feedback. So, a percentage measure of reputation in the regression model helps us to avoid any insidious effects of high degree of correlation in regression analysis. Similarly we find significantly high positive correlation between current price and lagged price. So, in the *PPF* equation we use an aggregate measure of lagged price that is the average unit price of products for all the sales up to the previous period. Our measures of errors and returns are also calculated per order on a cumulative basis. We employ the following lags in the structural model:

- in equation 1, %positive feedback is lagged by one period,
- in equation 2, weighted price and %errors and returns are lagged by one period,
- in equation 3, price is lagged by one period.

There are two reasons for using one-period lags of in all these variables. First, lags are obviously appropriate because of the high degree of correlation as mentioned before. Second, lags appropriately capture the dynamics of decision process facing consumers and the ABCE retailers and the nature of the aggregated data available to them. In the case of consumers, decisions to purchase from a retailer will depend on the feedback summarized online when the purchase decision is made. Thus, in the orders equation we use the one-period lag of %positive feedback. Given our level of aggregation it is not possible to capture any within-week effect of feedback on sales.

The determinants of feedback are modelled to include the weighted unit price of the product and the cumulative percentage of transactions that have an error or return associated with them, as well as controls for platform and holiday buying season.

In terms of the pricing equation, we recognize that ABCE merchants as a policy set one prices across all three platforms: Half, Amazon, and ABCE itself. Therefore, we recognize that seller pricing decisions cannot be platform specific, although demand may reflect platform-specific differences, especially if buyers have different levels of trust across the two reseller platforms. We hypothesise that current price is largely expected to reflect last period's prices (what the good sold for "last time") as well as the effects of any returned goods, as well as the platform and holiday controls.

We use iterated three stage least square (I3SLS) to estimate Model 1 with % errors and returns (*SER*) and all the lagged variables as instruments. The results of estimating Model 1 are presented in the first column of Table 3. Figures in bold indicate statistically significant estimates at the 5% level. In the order equation, there is a significant impact of price, feedback, and holiday season on demand. The impact of price is negative, though at a decreasing rate (i.e., the coefficient of price has a negative coefficient and price^2 has a positive coefficient). As expected, orders are higher during the holiday buying season. Finally, the percentage positive feedback has a positive and significant impact on orders. Since orders are measured in thousands, the results indicate that a 1% increase in percentage positive feedback will yield 2,400 additional orders per week – a very significant effect given the average number of orders per week in the dataset is 7929. On the other hand not all sales generate feedback. On the eBay platform, 60% transactions generate feedback and on the Amazon platform it is only 20% of the transactions. And at the time of our study, this retailer had approximately 250,000 feedback.

In terms of determinants of feedback, the platform controls are significant and significantly different in sales (V) and % positive feedback (PPF) but not in price (p) equation, confirming different effects across the two platforms. Significant differences in control in the first two equations suggest there can differences in demand behaviour and reputation formation mechanism under these platforms. The % of errors and returns (SER) is positive and statistically significant, though of a practically insignificant magnitude. This finding prompts us to explore the determinants of feedback in greater depth below. In the price equation, the sole significant result is the coefficient on lagged price, indicating that the pricing is largely a “naïve” replication of last period’s pricing.

To explore whether there is any differences in system generated errors and returns we then run the same structural model but disaggregating the SER variable into system errors (SE) and returns (R):

$$\begin{aligned}
&V_{it} = bin_{eV} + bin_{AV} + bin_{sV} + \upsilon_p p_{it} + \upsilon_{p2} p_{it}^2 + \upsilon_f PPF_{it} \\
&PPF_{it} = bin_{ePPF} + bin_{APPF} + bin_{sPPF} + \pi_{wp} wp_{it} + \pi_{SE} SE_{it} + + \pi_R R_{it} \\
&p_{it} = bin_{ep} + bin_{Ap} + bin_{sp} + \varphi_p p_{it-1} + \varphi_R RET_{it}
\end{aligned} \tag{1.2}$$

Result of this model are presented as Model 2 in Table 3. The results of Model 1 and 2 are qualitatively similar; however, errors per order and returns per order affect %positive feedback differently. Somewhat surprisingly, errors per order has a positive impact and returns per order, as expected, has a negative impact on the feedback generation process. Again we test of the differences in control for platform and again we find that in orders (V) and %positive feedback (PPF) equations they are significantly different.

To explore the differences of these two platforms we then estimate our structural model but using data from one platform at a time. Results of these two models are presented as Half Model and Amazon Model in Table 3. Given that the price formation and product assortment decisions are not platform specific, these two estimated models are potentially biased. These two models are estimated as first step to explore the differences across the platforms. Interestingly, we find that the effect of system errors to be very different at Half than at Amazon. Surprisingly, system errors/order have a significantly ***positive*** relationship with %positive feedback on the Half platform. That is, the more errors there are, the more positive feedback is received under the eBay mechanism.

To further explore the differences between the platforms we estimate the following modified structural model:

$$\begin{aligned}
V_{it} &= bin_{eV} + bin_{AV} + bin_{sV} + \upsilon_p p_{it} + \upsilon_{p2} p_{it}^2 + \upsilon_{fA} APPF_{it} + \upsilon_{fa} ePPF_{it} \\
APPF_{it} &= bin_{APPF} + bin_{sPPF} + \pi_{wp} Awp_{it} + \pi_{SE} ASE_{it} + + \pi_R AR_{it} \\
ePPF_{it} &= bin_{sPPF} + \pi_{wp} ewp_{it} + \pi_{SE} eSE_{it} + + \pi_R eR_{it} \\
p_{it} &= bin_{ep} + bin_{Ap} + bin_{sp} + \varphi_p p_{it-1} + \varphi_R RET_{it}
\end{aligned} \tag{1.3}$$

In this model we explicitly assume that %positive feedback affects total sales differently under two platforms. So, in our sales (V) equation we disaggregate the %positive feedback to %positive feedback generated at Amazon (APPF) and %positive feedback generated at eBay (ePPF) into these two new variables. Also, we assume that %positive feedback generation process is different under these two platforms. So, rather than having a single equation to explain feedback generation process in this model we define two separate %positive feedback generation function. Results of this structural model is presented in Table 4. In this model, we find that in the Amazon platform %positive feedback affects sales whereas on the eBay platform this measure of feedback has no impact on sales. On the Amazon platform, both errors and returns negatively impact %positive feedback but on the eBay platform system errors have significant ***positive*** impact while returns have the expected negative impact. These results suggest that the eBay reputation mechanism has no practical significance in generating consumer demand; additionally, processes that can cause consumer inconvenience may perversely generate ***positive*** feedback on Half.com.

To test for the best model fit we use the Vuong test (1989) and test each model against the other. Our test results suggest Model 3 is the best fitting model. Our results from the estimated models suggest that there are significant differences across the platforms in terms of how errors are generated and how feedback-based reputation affects sales or demand for the products. To explore this surprising difference across these two platforms we conduct exploratory data analysis using disaggregated data.

The Causes for Differences

As mentioned before, there are two key differences between these mechanisms: the range of the rating scale and reciprocity of rating. Here we first hypothesise how certain underlying differences in design of these two marketplaces can lead to significant differences in feedback generation process and its impact on sales:

Scale Effect:

H1: A five-point scale should result in less use of the end points than a three-point scale

Reciprocity Effects:

H2: A two-way rating system will result in much higher % positive and much lower % negative than a one-way rating system

H3: A two-way rating system will make buyers much more likely to leave feedback (in order to elicit feedback in return) than buyers using a one-way rating system.

In addition, we believe that consumers will come to recognize the differences across the mechanisms implied by hypotheses 1-2. As a result, we predict a different impact of feedback on demand across the Half and Amazon platforms. In particular, since the vast majority of feedback observed under the eBay reputation mechanism is positive, we expect a "ceiling effect" on Half.com. Thus, we anticipate that positive feedback will have less effect on Half than on Amazon in terms of inducing demand either in quantity or price.

Ceiling Effect:

H4: Buyers on the Half platform will be less sensitive to positive feedback than buyers on the Amazon platform.

Finally, we believe that the platforms themselves will create different expectation for buyers. Amazon.com is noted for its culture of "customer obsession" instilled by the founder Jeff Bezos, which has resulted in industry-leading fulfillment and customer satisfaction. Amazon.com has been consistently rated the number one business in the world in terms of service quality as measured using the SERVQUAL instrument (cite). On the other hand, buyers on Half.com know that they are dealing with a community of individual sellers, most of whom are small in size. Even if these sellers are completely honest, they cannot be expected to be as efficient or competent as Amazon.com in terms of merchandising or fulfillment, and buyers will be aware of this difference. Thus, we believe that buyers will have different expectations for customer service across the two platforms; in particular, Amazon buyers may react more strongly to any problems that arise.

Expectation Effect:

H5: Buyers on the Amazon platform will be more likely to leave negative feedback as a result of an error or return than buyers on the Half platform.

Analysis of Differences

The frequency of positive, neutral, and negative feedback over time across the Amazon and Half platforms is depicted in Figure 1. In terms of distribution across the rating scale, some 94.71% of feedback under the eBay system uses the endpoints (positive or negative); very little feedback is neutral. If feedback were evenly distributed across the categories, of course, we would expect only 2/3^{rds} of the feedback on eBay to be in the endpoint categories. On Amazon, 83.78% of the feedback uses the endpoints (1 or 5); only 16.22% of the feedback is spread over the three middle categories (2, 3, 4). Again, the naïve expectation of uniform distribution would lead us to expect only 2/5^{ths} of feedback on Amazon to be in the endpoint categories. While the use of endpoint feedback is, indeed, lower under Amazon than under eBay, the difference is smaller than would be expected under most distributions of true population feedback (e.g., uniform, normal). Thus, we find weak support for H1.

As can be seen, the feedback on the Half platform is significantly more positive and less negative than that on the Amazon platform. Indeed, the percentage of negative feedback on Amazon is more than three times as high as on Half, providing evidence of the "positive bias" previously noted with the eBay mechanism. To compare this difference, we construct feedback scores for individual ABCE merchants, operationalized as the percentage of feedback that is positive for all ABCE sellers having at least 20 feedback items on both the Amazon and Half platforms. There are 1,537 sellers having at least 20 pieces of feedback on each platform, and a t-test on the difference between the Amazon and Half percentage positive for each seller strongly rejects the null hypothesis ($t = -15.4640$, $p < 0.0001$). Thus, H2 is strongly supported.

One other basic comparison between the Amazon and eBay mechanisms relates to the propensity of users to leave feedback. In order to calculate this number, we obtained the total number of transactions conducted by ABCE sellers on the two platforms during our data in question. The differences in the likelihood of receiving feedback across the two platforms was striking: on average, only 17.9% of transactions on the Amazon platform received feedback, whereas 60.1% of transactions on the Half platform received feedback. This very large difference supports H3. The likelihood of feedback over time for each platform is depicted in Figure 2.

We attribute these very large differences in the type and frequency of feedback across the two platforms to the one-way versus two-way rating systems. Under the eBay mechanisms, buyers rate sellers, but sellers also rate buyers, and buyers know this; game theory predicts a reciprocal relationship to emerge. Indeed, this is one explanation for the overwhelmingly positive feedback on eBay: there is no incentive to leave negative feedback lest the other party retaliate with negative feedback, thereby damaging both reputations. Indeed, always leaving positive feedback can be construed as a dominant strategy on eBay.

The earlier structural models have already tested and confirmed hypotheses 4 and 5. Supporting H4, we find that positive feedback on Half has no effect on demand, whereas positive feedback on Amazon has a positive and significant relationship to demand (Model 3). Supporting H5, we find that buyers on Amazon are more sensitive to fulfillment problems, and are more likely to leave negative feedback when such problems (errors or returns) arise than are buyers on Half. In fact, buyers on Half are, perversely, more inclined to leave positive feedback when system errors occur.

Conclusions

Our ultimate objective is to derive a richer understanding of the impacts of the dimensions of reputation mechanism on online transactions in both the retail and auction contexts. In this study, we have taken first steps to exploring this difference, and, to some extent, have generalized earlier findings about online reputation effects that were derived solely from the eBay platform. In particular, we find quite different propensities to leave feedback and resulting impact of feedback across the eBay and Amazon mechanisms. Our analysis suggests that the Amazon mechanism appears to elicit much more unbiased feedback than does the eBay mechanism, resulting in reputations that are more useful to buyers.

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Figure 1: Path Diagram of the Structural Model

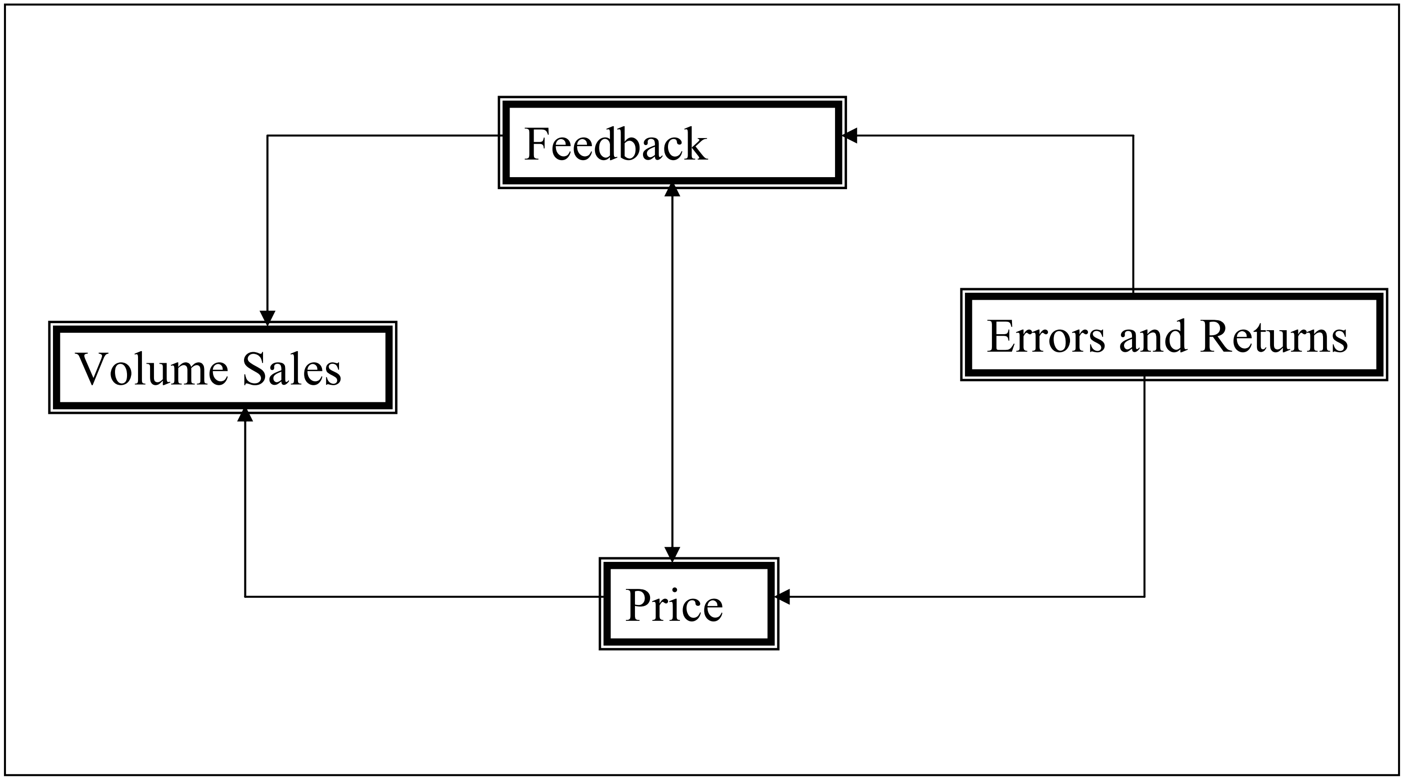

Figure 1: Feedback by Platform over Time

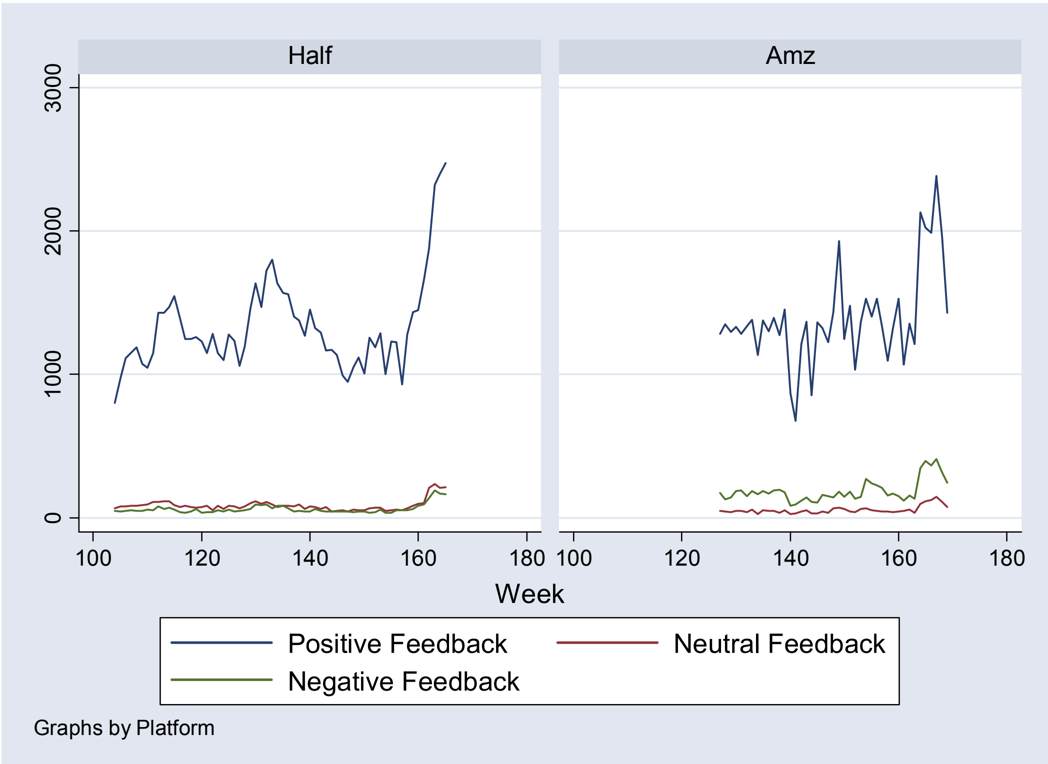

Figure 2: Unit Sales ('000) by Platform over Time

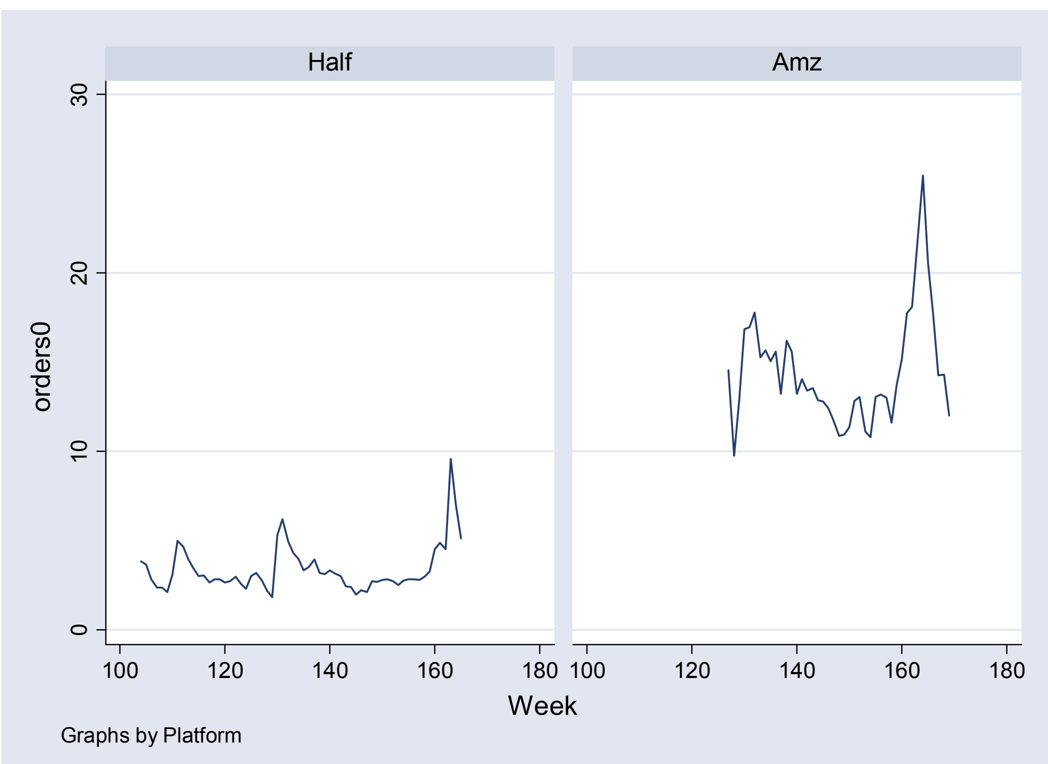

Figure: Unit Price by Platform

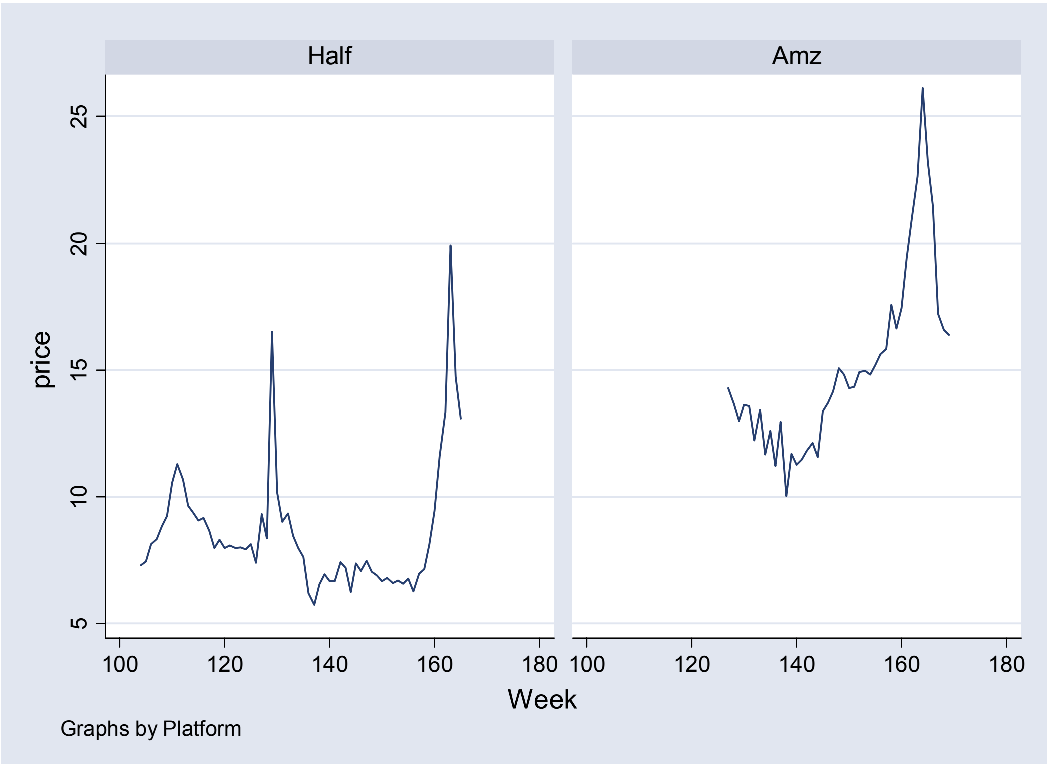

Figure 3: Mean price by Feedback Type and Platform

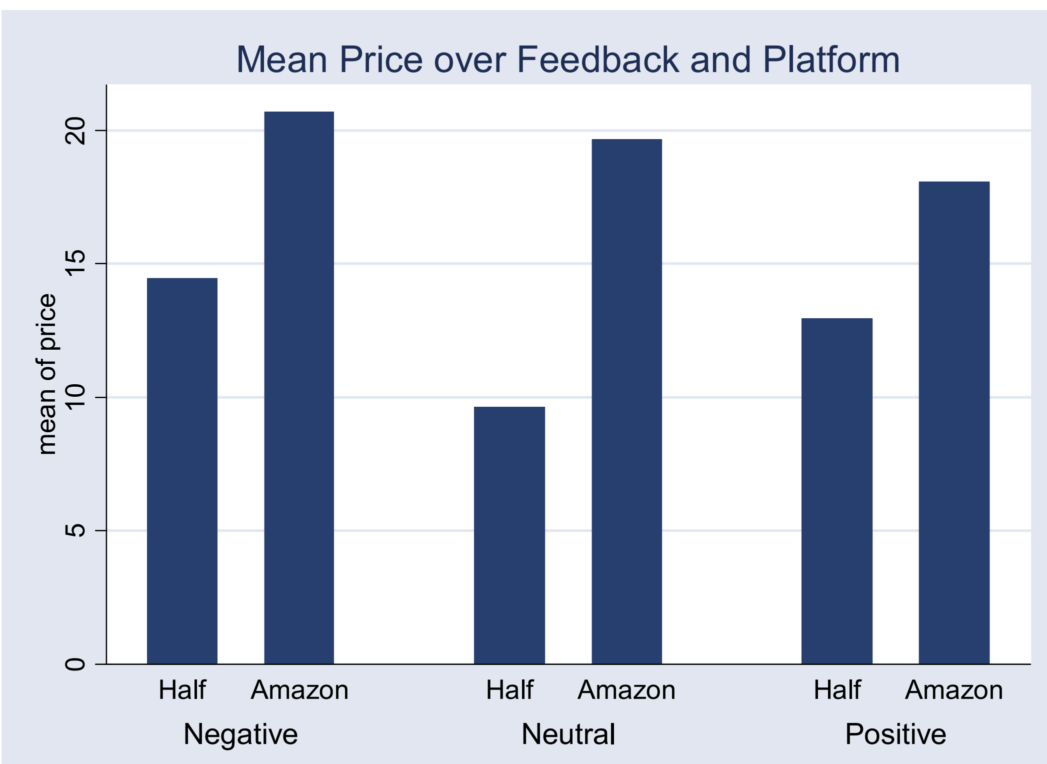

Figure 4: Mean Price over Transaction Details and Platform

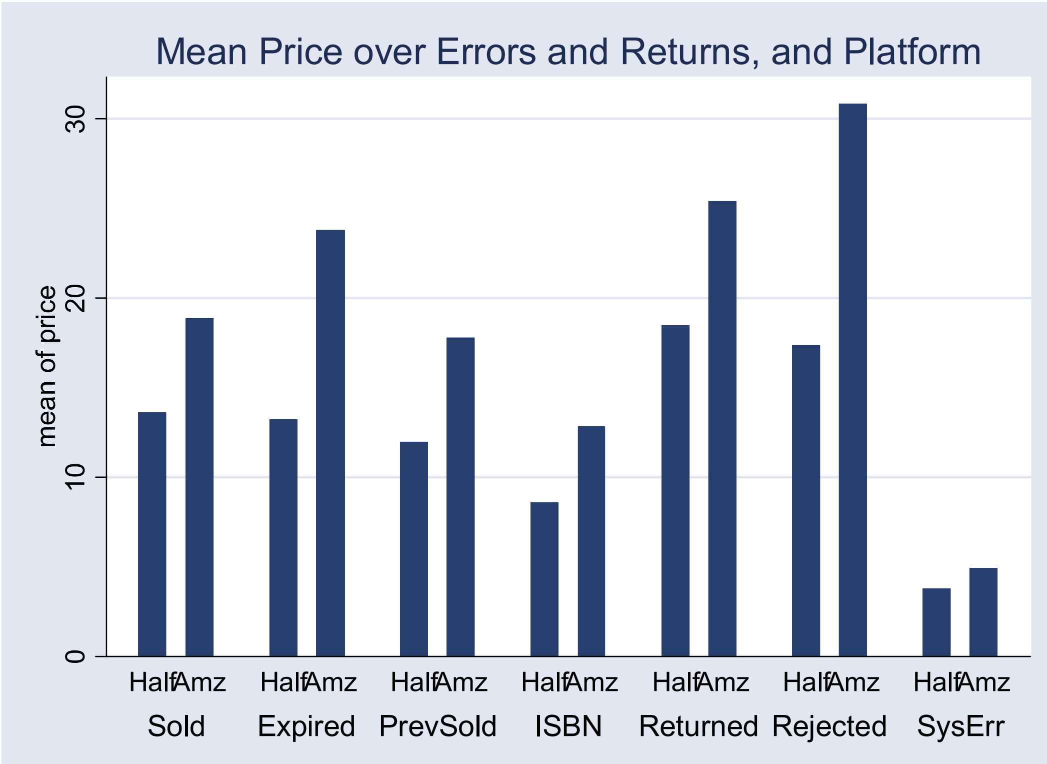
Mean Price over Errors and Returns, and Platform
mean of price
0
10
20
30
Half
Amz
Sold
Expired
PrevSold
ISBN
Returned
Rejected
SysErr

Figure 5: Feedback Frequency by Transaction Details and Platform

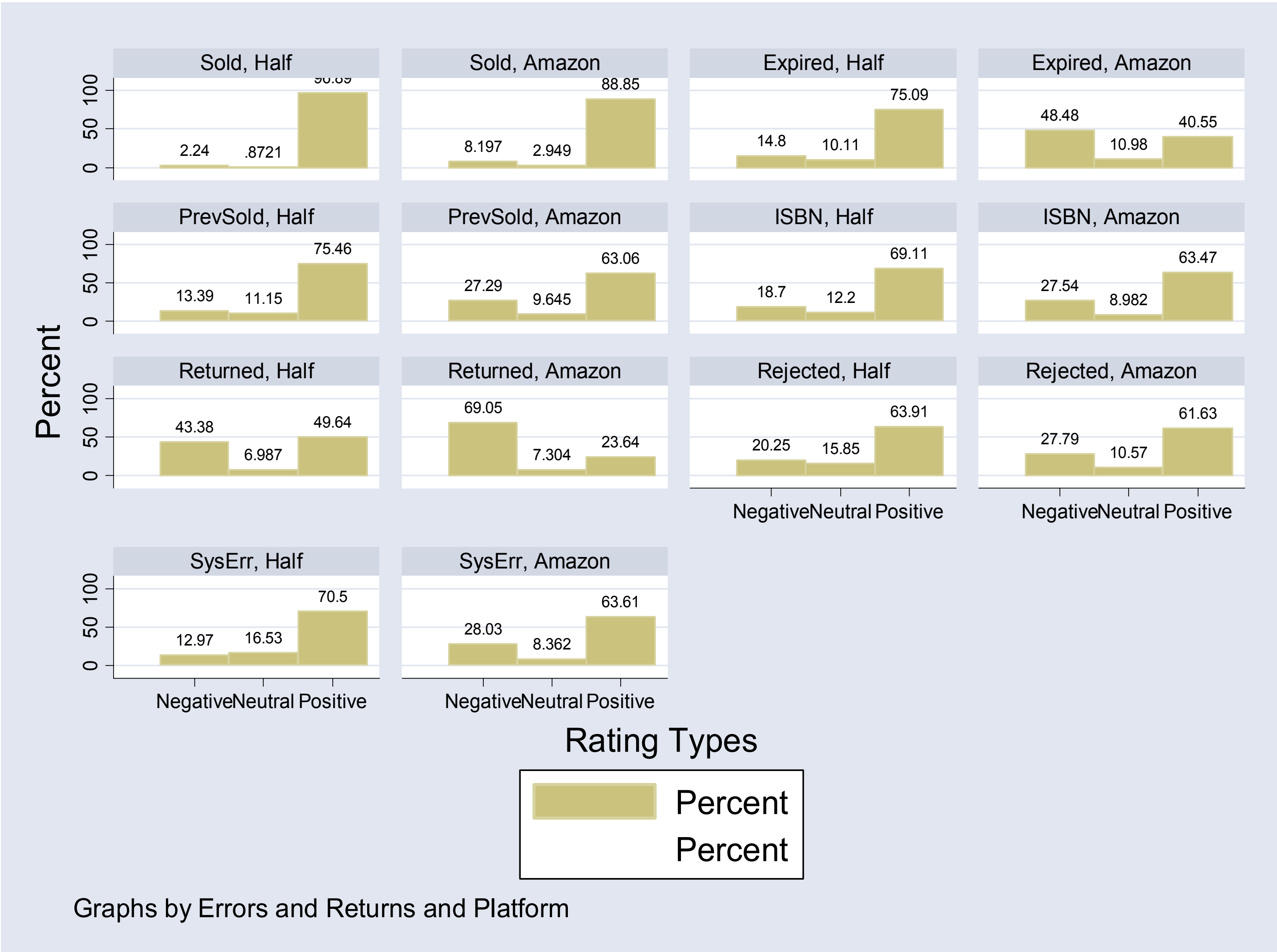

Table 1: Total Feedback on the Amazon and Half Platforms

	Amazon		Half	
	N	%	N	%
Positive	69966	85.2%	123446	90.5%
Negative	9463	11.5%	5695	4.2%
Neutral	2656	3.2%	7219	5.3%
Total	82085	100%	136360	100.0%

Table 2: Feedback Data Matched with Sales Data

	Amazon		Half	
	N	%	N	%
Positive	59458	86.5%	98059	90.6%
Negative	2016	10.6%	3816	3.9%
Neutral	7281	2.9%	1011	5.5%
Total	68755	100%	102886	100.0%

Table 3: Three-Equation Structural Model

	Variable	**Full Model 1**	**Full Model 2**	**Half Model**	**Amazon Model**
Equation: Orders	Binary: Half	**-132.16**	**-95.50**	65.14	
	Binary: Amazon	**-119.74**	**-82.24**		120.82
	Unit Price	**-1.10**	**-1.66**	**-0.77**	**-3.77**
	Unit Price Square	**0.05**	**0.06**	**0.05**	**0.11**
	Seasonal Binary	**2.44**	**2.61**	**1.70**	**4.14**
	Lagged % Positive Feedback	**1.56**	**1.19**	-0.66	-0.87
Equation: % Positive Feedback	Lagged Average Price	**-0.32**	**-0.30**	**-0.28**	**-0.19**
	Binary: Half	**93.01**	**92.66**	**92.38**	
	Binary: Amazon	**90.36**	**90.24**		**95.15**
	Lagged % (System Errors and Returns/Orders)	**0.00**			
	%(Errors/Orders)		**0.06**	**0.06**	**-0.07**
	%(Returns/Orders)		**-0.53**	-0.54	**-4.02**
Equation: Price	Binary: Half	-4.01	18.36	**-177.34**	
	Binary: Amazon	-2.20	19.91		**1851.58**
	Seasonal Binary	0.81	0.71	**0.07**	**1.75**
	Lagged % Positive Feedback	0.08	-0.18	2.01	**-18.93**
	Lagged price	**0.74**	**0.74**	**0.55**	**0.49**
	Lagged Returns to System Errors	-0.76	-0.09	-0.09	**-145.18**

Table 4: A Four-Equation Structural Model

	Variable	Full Model 3
Equation: Orders	Binary: Half	7.68
	Binary: Amazon	**-182.58**
	Unit Price	**-1.16**
	Unit Price Square	**0.05**
	Seasonal Binary	**2.32**
	Lagged % Positive Feedback (Amazon)	**2.26**
	Lagged % Positive Feedback (Half)	0.01
Equation: % Positive Feedback (Amazon)	Lagged Average Price	**-0.20**
	Binary: Amazon	**94.93**
	Lagged % System Errors (Amazon)	**-0.08**
	Lagged % System Returns (Amazon)	**-3.73**
Equation: % Positive Feedback (Half)	Lagged Average Price	**-0.32**
	Binary: Half	**92.82**
	Lagged % System Errors (Half)	**0.06**
	Lagged % System Returns (Half)	**-0.55**
Equation: Price	Binary: Half	23.13
	Binary: Amazon	24.80
	Seasonal Binary	0.67
	Lagged % Positive Feedback	-0.23
	Lagged price	**0.71**
	Lagged Returns to System Errors	-0.14