Financial Value of Reputation: Evidence from the eBay Auctions of Gmail Invitations*

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Abstract

In a marketplace of repeated transactions with asymmetric information, theory predicts that sellers with a good reputation have a higher probability of sale and receive a higher transaction price. In this paper, I test this theory using more than 55,000 auctions of "Gmail invitations" on eBay, essentially a market of homogeneous goods with non-enforceable contracts. This is an ideal environment to test the theory because it allows a clean separation of the reputation effects from other controlling factors. This study provides evidence in favor of the theoretical predictions because sellers who improve their reputation from the lowest to the next quintile experience a 6.2% higher probability of sale and a 6.1% hike in the implied buyer valuation after adjusting for truncation bias from failed auctions and explicitly controlling for seller skills. This study also shows that in addition to a dimension of reputation universal across different product markets, the product-specific dimension of reputation significantly affects the auction outcomes.

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1 Introduction

When counterparties of a transaction have asymmetric information about the goods or services being traded, there is a possibility that the transaction could fail. One way to avert such a market collapse because of the "lemons problem" is to balance some form of reputational penalty against acts of abusing the relative information advantage. In light of the seminal work by Akerlof (1970) and as detailed by many researchers since, few would dispute the notion that reputation works as a signal for quality and thus should be positively associated with price in a market setting with information asymmetry, especially one with repeated transactions.[1]

Intuitively, it makes sense that the cost of nurturing a good reputation should be offset by the financial rewards of maintaining the good reputation. However, no matter how receptive we are to the notion that reputation signals quality and thus matters at the theoretical level, it remains empirically challenging to associate financial value with reputation. The main empirical difficulties with establishing such an association lie in the elusive nature of reputation. Reputation is hard to measure and tough to isolate from other factors that also shape transaction outcomes.

The goal of this paper is to identify a setting that naturally overcomes these empirical challenges and present sufficient evidence verifying a positive relationship between price and reputation. Ideally, we would like to examine a continuous marketplace with a clean separation of the seller's reputation effect from other competing factors. The market has to be liquid enough to generate sufficient transaction data and provide a good benchmark price for the underlying goods. Only with a reliable benchmark price series can we attempt to decompose the settlement price into components that are attributable to reputation effects and those that are not related to reputation. Moreover, the goods being traded have to be simple enough to prevent ambiguity over the characteristics of goods being traded; otherwise, uncertainty over the product condition or product quality can also influence transaction outcomes.

The auction of Gmail invitations on eBay works well as such a setting because this market fulfills all of the above conditions. In this study, I focus on the influence of the seller's reputation on auction outcomes because the buyer's reputation plays a very limited role here. This is a very active market with 55,094 auctions listed during the three-month study period, averaging more than 25 auctions per hour. The abundance of transaction data in this study makes it feasible to construct a market price index at very high frequency so as to control for the fluctuation of market value over time. The subject of the auction, a Gmail invitation, is essentially a web link with a unique 21-character alpha-numeric string that enables the owner to create an account for free email service (also known as Gmail) provided by Google Inc. The extremely homogeneous nature of the auction subject largely eliminates the product complexity evident in other auction studies. Instead

[1] See Kreps and Wilson (1982), Kreps et al. (1982), Fudenberg and Kreps (1987), Diamond (1989), Fudenberg and Levine (1992), Tirole (1996), Holmström (1999), Tadelis (1999, 2002), Gomes (2000), Mailath and Samuelson (2001), and Bar-Issac (2002), among others.

of worrying about whether the goods delivered match the type and quality condition described by the seller, buyers in this market face only one form of uncertainty after making the payment – whether or not the seller will deliver a functioning Gmail invitation as promised. Thus seller reputation serves as a clean signal for quality in this context and should be quite relevant for rational buyers as they participate in an auction.[2]

Since not all auctions go successfully, the truncation bias resulting from failed auctions often presents another challenge due to concealed buyer valuations in such cases. While this is a very important concern in many empirical studies of eBay auctions with low success rate, this paper suffers little from this bias because on average about 90% of listed auctions in my sample were completed successfully. I also consider a valuation bound for failed auctions in this paper, further mitigating the truncation bias.

Reputation is gained and lost through actions of the carrier, so it is natural to measure reputation based on past actions. All participants of eBay auctions have a feedback profile that is publicly accessible. At the end of each auction, the buyer and the seller can rate each other on a three-level scale – positive, neutral or negative. The cumulative number of positive feedback net of negative feedback becomes the Feedback Score. This score is the base line measure of reputation in this and many other studies. I have termed it "universal" reputation in this paper given the equal weights of feedback assigned by eBay across all product markets. I also introduce a second measure of reputation to account for the specificity of product types where the reputation is established. The idea is that a seller who built a strong reputation by selling postcards on eBay may not have the same credibility when selling Gmail invitations despite a high feedback score. By restricting the reputation measure to only past auctions of Gmail invitations, this paper achieves a product-specific distinction from the feedback score based on all past auctions. I have termed this new and more focused measure "product-specific" reputation or "specialty" reputation.

The main finding of this paper is that both the universal and the product-specific reputation have a substantial effect on auction outcomes. In this sample, sellers who improve both measures of reputation from the lowest to the next quintile experience a 6.2% higher probability of sale and a 6.1% hike in buyer valuation, after adjusting for the truncation bias from failed auctions and explicitly controlling for seller skills. This finding is consistent with the theoretical prediction of a positive relationship between the seller's reputation and the transaction price (see Klein and Leffler, 1981; Shapiro, 1983; Allen, 1984; and Houser and Wooders, 2006).

This paper makes an important contribution to the literature of eBay auctions because extant empirical studies have failed to reach a consensus on the effectiveness of the reputation system in eBay.[3] The lack of consensus partly arises from the heterogeneous nature of the auction items

[2] Jin and Kato (2006) argue that a positive relationship between price and reputation validates the theory only if "the true quality is perfectly observed after transaction and the observation helps update the reputation." The sample of Gmail invitations easily satisfies this condition.

[3] For example, Camerer and Weigelt (1988) provide experimental evidence in support of the positive reputation

because the effect of a seller's reputation can differ across goods with different product types and across different conditions of goods even in the same product category. The lack of consensus is also affected by the fact that there is no perfect way to measure the buyer's valuation on failed auctions. In a sharp contrast, the marketplace in this paper provides a fairly ideal environment to study reputation effects because it allows us to bypass the common challenges in existing studies. Moreover, having the nearly-exhaustive auction history of Gmail invitations makes it possible to build the product-specific dimension of reputation and separate its pricing effect from that of the traditional measure of reputation based on the auction records of all products. This paper shows that studies without accounting for the product-specific dimension of reputation can suffer from an omitted variable bias.

The empirical difficulties with establishing reputation effects are not unique to the eBay auctions setting. Diamond (1989) presented a theory of reputation formation in debt markets and Gorton (1996) tests this theory in the bank notes market. As Gorton sees it, "[t]he main problem in empirically testing for the presence of reputation effects is that a counterfactual is posed: [it] requires knowing what the [price] would be if the same firm had a reputation." In other words, it is difficult yet necessary to find borrowers that are identical in every aspect except in their credit histories. The key to testing reputation effects is to identify a market setting where the only distinguishing factor for quality concerns is the agent's reputation, everything else being equal.

Therefore, the positive finding of reputation effects in a highly homogeneous product market also contributes to our understanding of the role that reputation plays in the market of banking products as well as other non-auctions market. The finding of this paper in fact serves as a very conservative estimate of reputation effects because counterparties in a more complex market have a stronger need for using reputation as a quality signal for unobservable characteristics. In other words, a good reputation should be valued even higher in complex markets than in the eBay auction of Gmail invitations.

While the identification strategy of this paper relies on the eBay auction of Gmail invitations, value implications of reputation apply more broadly. For instance, Gomes (2000) theoretically demonstrates that in the equity market the controlling shareholders can establish a good reputation for not expropriating the minority shareholders. As a reward, such firms are more likely to go public and enjoy higher stock prices. On the empirical side, Benveniste et al. (1992) argue that reputation

effect on price, and Ba and Pavlou (2002) show in another experiment that positive feedback increases price, but negative feedback does not matter. Also in a controlled experiment, Resnick et al. (2006) show that positive feedback increases the sale price yet negative feedback seems to have no price effects. Lucking-Reiley et al. (2007) find no effect from positive feedback and a negative effect from negative feedback on price. Melnik and Alm (2002) and Houser and Wooders (2006) find that positive feedback increases the price and negative feedback decreases the price. Resnick and Zeckhause (2002) find that both positive and negative feedbacks affect the probability of sale but not the sale price of successful auctions. Bajari and Hortaçsu (2003) demonstrate that both positive and negative feedback affect the probability of bidder entry in a structural model, but only positive feedback has an impact on price. McDonald and Slawson (2003) present evidence that higher prices are associated with an increase in the number of positive comments relative to negative ones. See Dellarocas (2003), Bajari and Hortaçsu (2004) and Resnick et al. (2006) for surveys of empirical studies on reputation effects.

can be established through repeated interactions between brokers and specialists and thus reduce the effects of asymmetric information. Madhavan and Cheng (1997) show that reputation can affect the transaction price in block trading. Battalio et al. (2001) present evidence of price discrimination by market makers who knew the broker identity. Massa and Simonov (2003) also demonstrate that the differentiation in reputation of traders can be linked to different volume and volatility patterns in the Italian Treasury bond market. This paper provides corroborating evidence that reputation plays an important role in the market design precisely because of its price impact.

There exists a large literature of empirical studies on reputation effects, and Dellarocas (2003), Bajari and Hortaçsu (2004) and Resnick et al. (2006) provide excellent surveys. This study is closely related to four recent papers, Dewan and Hsu (2006), Jin and Kato (2006), Lucking-Reiley et al. (2007) and Dimoka and Pavlou (2008). Although these four papers also study the influence of seller reputation on the probability of sale and the implied buyer valuation using auctions on eBay, my paper is different in four ways.

First, the subject of auctions in this paper is truly unique in that it largely eliminates buyers' concern over the true condition or quality of products. In contrast, buyers would naturally worry about the condition of goods such as stamps (the subject in Dewan and Hsu, 2006), baseball cards (the subject in Kin and Kato, 2006), coins (the subject in Lucking-Reiley et al., 2007) or used cars (the subject in Dimoka and Pavlou, 2008). The physical qualities of products are often difficult to determine even with professional help from well-recognized third parties, and misleading quality claims by some sellers make the situation even worse. The extreme uncertainty about quality conditions may not be sufficiently addressed by seller reputation, as Jin and Kato (2006) show that reputable sellers do not provide goods of better quality conditional on completed auctions. The Gmail invitations are so homogeneous that it removes such uncertainties buyers typically face, especially among auctions with less homogeneous goods. It leaves buyers with just one concern over whether or not the seller would honestly deliver the product after the transaction. Jin and Kato (2006) demonstrate that this is where seller reputation on eBay shines in terms of signaling the genuine delivery of the goods.

Second, this paper demonstrates the empirical importance of controlling for the product-specific dimension of seller reputation. Though accounting for product-specific reputation is not entirely new from a conceptual point of view (see Jin and Kato, 2006), there is only one other paper to my knowledge that empirically considers the "specialty" reputation.[4] Specifically, Dimoka and Pavlou (2008) include the number of past sales of used cars on eBay as a control for seller characteristics

[4] The notion of product-specific seller reputation here is different from the product uncertainty that is the main focus of Dimoka and Pavlou (2008) and Ghose (2009). While the product-specific seller reputation essentially amounts to a measure of leadership status or market share for the seller, the product uncertainty involves the quality condition of physical and durable goods that is difficult for the seller to convey in a reliable way over the electronic trading platforms such as Amazon and eBay. These authors make a convincing case over the empirical importance of separating seller uncertainty from product uncertainty in the context of used cars in eBay and used electronic products in Amazon, respectively. As mentioned earlier, the study subject in this paper is both intangible and extremely homogeneous, thus severely curtailing the potential role that product uncertainty can play in this particular context.

and omit reporting its empirical effect. Like many studies in this literature, Dewan and Hsu (2006) and Lucking-Reiley et al. (2007) only measure reputation by the feedback score as defined by eBay. Jin and Kato (2006) rightly criticize eBay's practice of assigning equal weights to comments left on goods in different product categories, goods with different transaction values, and users with different roles (buyers versus sellers). Although this paper shares with Jin and Kato (2006) in emphasizing the need for differentiating product markets in the process of reputation formation, data limitations in their sample prevents them from empirically testing this new dimension of reputation. Having the entire auction history of Gmail invitations available makes it possible to measure the seller's reputation established in the market of Gmail invitations alone, and I show in this paper that the Gmail specialty reputation significantly affects the auction outcomes.

Third, I use different techniques in this paper to deal with the truncation bias associated with failed auctions. As of this writing, Dimoka and Pavlou (2008) study only those successful auctions and do not address the truncation bias. In contrast, Dewan and Hsu (2006) use the Tobit model, Jin and Kato (2006) use the propensity score as well as the Heckman two-step procedure, and Lucking-Reiley et al. (2007) use the censored-normal model to address the truncation bias. The success rate of auctions in this sample (about 0.90) is higher than those four papers (about 0.20 for used cars in Dimoka and Pavlou, 2008, and about 0.65 for the other three papers), and thus the scope of the truncation bias is limited here. Nevertheless I use the interval regression framework to obtain a valuation bound for failed auctions that is tighter than using minimum bids alone. This methodology further reduces the truncation bias.

Finally, this paper explicitly measures seller skills by quantifying the effectiveness of all auction titles. Specifically, I text-mine each auction title to determine whether the seller promoted the auction in any of six broad categories, and use the total number of categories of promotion within each title as a proxy for seller skills. The resulting composite measure has only marginal impact on the probability of sale, but positively affects the buyer's willingness to pay even after adjusting for truncation bias. The positive relationship between seller skills and price is both statistically and economically significant. This paper makes an important contribution to the extant literature by directly addressing the concern in Resnick et al. (2006) that many empirical studies on eBay suffer from an omitted variable bias due to lack of control for seller skills. This paper's method of measuring seller skills by quantifying the effectiveness of auction titles can be easily implemented in other empirical studies.

The balance of the paper proceeds as follows. In Section 2, I provide some institutional details about eBay auctions in general as well as the background of Gmail invitations, and explain the empirical strategy of this paper. Section 3 presents the data source and summary statistics, followed by the main findings in Section 4 and the conclusion in Section 5.

2 Empirical Strategy

In this paper, I study reputation effects using more than 55,000 auctions of Gmail invitations on eBay. Before explaining why this sample is especially suitable for this type of study and how the empirical tests are designed in this paper, I provide some institutional background for eBay auctions and Gmail invitations.

2.1 eBay Auctions

As one of the most successful on-line auction sites, eBay Inc. built an internet trading community with 86.3 million active users worldwide as of the end of 2008. For the year of 2008, eBay reported net income of $1,779 million on revenue of $8,541 million.[5]

In a typical auction on eBay, the seller describes the item for sale, chooses a fixed number of days to display the listing, and specifies the payment method and shipping policy (if applicable). The seller can also specify a secret reserve price.[6] Buyers can type some keyword into the search box on eBay's website so that a list of relevant auctions shows up, or they can browse the listings according to the product categories. Once buyers decide to participate in an auction, they set the maximum bidding price and a set of proxy bids with incrementally higher values are automatically submitted on their behalf. Before the auction ends, buyers are notified by email when their maximum bidding price is outbid by another buyer, and have the opportunity to increase the maximum price in order to continue bidding for the auction. At the close of the auction, the highest bidder wins the auction and pays for the second highest bid plus a fixed increment. The seller pays eBay a listing fee plus a fixed percentage of the sales revenue if available.

Many observers largely attribute eBay's success to its innovative reputation monitoring system that is designed to induce sellers to provide a quality experience.[7] The core of this system is the user-specific feedback profile that is publicly accessible. Following the conclusion of each auction, the goods are delivered, the payment is settled, and eBay invites all participants of the auction to rate each other within 90 days on the quality of the transaction experience. In addition to leaving a brief comment in text, users are advised to rate their trading partners on a three-level scale – positive, neutral or negative. Every eBay user carries a measure called the Feedback Score that is the total number of members who provided positive feedback net of the number of members who left negative feedback. The feedback score is prominently displayed after each user's nickname, with a link to the entire feedback profile that everyone can view. On the feedback profile, all past auctions are listed in reverse chronological order, along with brief information such as the auction

[5] These figures are based on the annual report for 2008 that eBay Inc. filed with Securities and Exchange Commission on February 20, 2009.

[6] Vincent (1995) justifies the practice of keeping the reserve price private as one way of offsetting the discouragement to bidder participation caused by a reserve price.

[7] See Lucking-Reiley (2000) for an introduction to the general mechanisms of internet auctions, and Resnick et al. (2000) and Resnick and Zeckhauser (2002) for more details.

identification number, the usernames of the buyer and the seller, the rating and the comment. The auctions closed within the preceding 90 days also have a web link to the actual auction listing and bids history.

2.2 Gmail Invitations

Gmail invitations are the result of a unique and successful marketing campaign that the internet search engine Google Inc. initiated on March 31, 2004 to promote its free email service (also known as Gmail). At that time, the development of Gmail services was still on-going and at an early stage. Google decided to open this free service to a limited set of users for testing purposes, and the early adopters were mostly its internal employees. To expand the pool of users in a gradual and controlled manner, Google issued electronic invitations to existing users who could send the invitations as gifts to family members or friends. The Gmail invitations were issued free of charge and each consisted of a web link with a unique 21-character alpha-numeric string that can be used exactly once. The recipient of each Gmail invitation was entitled to a free email account at Google, and the possession of a valid Gmail invitation was the only way to sign up for Gmail. As time went by, each Gmail user got incrementally more invitations to spread around and thus the pyramid of Gmail users continued growing via "word of mouth" at virtually no advertising cost for Google.

Relative to the incumbent providers of free web email services, the Gmail service had a few unique features and thus became instantaneously popular. At the time of announcement, Gmail allowed its users to store a lot of email messages, promising a storage capacity that was 250 and 500 times the space offered by Yahoo! Mail and Microsoft Hotmail, respectively. Gmail was also innovative in providing a built-in search function that allows its users to search through archived email messages in a manner as easy as a web search. Another advantage to early adopters of Gmail was the abundant choices of username available. Namely, the first John Doe who signed up for Gmail got to keep the john.doe@gmail.com account if he so desired while all late comers with the same name would have to find some variation of usernames that would potentially be less memorable.

Indeed, the ownership of a Gmail account soon became a bragging right (see Musgrove, 2004), and Gmail invitations became a hotly pursued commodity shortly after its introduction. On April 29 of 2004, the first auction of a Gmail invitation appeared on eBay and was sold for $35. Henceforth, Gmail invitations were routinely auctioned off on eBay and reached a price as high as $200 per invitation. The eBay auction of Gmail invitations formed a very liquid market, where 63,378 Gmail invitations exchanged hands at a total value of $393,027 over a three month period. I now turn to the rationale behind choosing this market to study reputation effects.

2.3 Distinctive Features

The eBay auction of Gmail invitations qualifies as an ideal setting to study reputation effects because this sample has several distinctive features that overcome many hurdles for empirical studies in this literature. The auction item is homogeneous in every aspect, and there are abundant trading data available. The nearly exhaustive auction history of Gmail invitations has a much lower fraction of failed auctions compared to other studies, and the entire history makes it possible to track the product-specific component of reputation. Lastly, the participants in an eBay auction of Gmail invitations engage in a non-enforceable contract and thus the role of seller reputation is non-trivial. I explain below some details of these unique features.

A Gmail invitation is essentially a web link with a unique code that enables the recipient to sign up for one Gmail account, an auction subject that achieves product standardization almost to the extreme.[8] The vast majority of Gmail invitations sold on eBay were delivered through email, so this sample cuts out the shipping and insurance considerations that are often necessary in auctions of physical goods. The homogeneous nature of the auction item in this sample overcomes the main hurdle in eBay studies that requires a clean separation of reputation from product differentiation such as different product types, different quality conditions of the product, different shipping and insurance policies, or different seller skills in describing the auction subject, etc.

This sample consists of 55,094 auctions over a three-month period; it is one of the largest sample sizes in empirical studies of eBay auctions. Given the abundance of transaction data, I am able to construct a market price index for Gmail invitations at very high frequency (e.g., hourly) and thus better control for the changing value of a Gmail invitation over time. Previous studies recognize the importance of using some form of book value as a control variable, but data limitations often force those studies to sample the book value much less frequently and rely on an entirely different data source for book values that may not reflect the latest transaction value.

Another hurdle in extant literature concerns the truncation bias arisen from failed auctions. There is no easy way to infer the buyer valuation on failed auctions, so studying only the successful auctions will lead to a biased estimate of the price impact of seller reputation. This problem becomes more severe among auctions with very low success rate. However, because Gmail invitations were hotly pursued at the time, the very high success rate in this sample (about 90%) limits the role of truncation bias.

As briefly discussed earlier in the Introduction, specialty reputation may help to separate sellers who formed reputations primarily in the auction of Gmail invitations from sellers who gained reputations in the auction of other types of goods. For instance, sellers who are good at selling

[8] The residual heterogeneity among Gmail invitations is negligible. A Gmail invitation expires three weeks after its issuance date. Strictly speaking, two Gmail invitations with different expiration dates should be considered as two different products. This is not a problem, however, for sellers who received their Gmail invitations directly from Google Inc. because they have the option of issuing the invitation after the auction is sold. Note that the description for the vast majority of auctions omitted mentioning the specific expiration date for Gmail invitations on sale.

postcards may not have an advantage at selling Gmail invitations, all else being equal. Having the entire auction history of Gmail invitations available here makes it possible to build a measure of reputation that is specific to Gmail invitations.

Finally, this sample involves non-enforceable contracts so rational buyers should carefully consider the seller's reputation upon bidding on an auction. The auction of Gmail invitations involves a non-enforceable contract partly because eBay does not provide any protection for buyers of intangible items. Gmail invitations are essentially web links and thus electronic (i.e., intangible) in nature. The non-enforceability aspect is also partially attributable to the fact that buyers who pay by credit cards receive no protection from the card issuers either. It is a common practice among credit card companies to deny payment disputes unless the payment exceeds \$50. The threshold of \$50 is a high ceiling for the vast majority of Gmail invitations in this sample, which have an average price of \$7.29.

In summary, the sample of Gmail invitations auctioned on eBay provides an ideal environment for the empirical examination of reputation effects. The market of homogeneous goods with non-enforceable contracts helps this paper to separate seller reputation from other factors that also influence the auction outcomes.

2.4 Empirical Design

I use two measures of reputation in this study. The baseline measure, *ebayscore*, is the quintile of the Feedback Score among all sellers, with 0 for the lowest quintile and 4 for the highest. I retrieve the entire archived feedback profile for each seller and repeatedly compute the Feedback Score as the cumulative number of positive comments net of negative comments from distinct users as of the auction closure time specified by the seller.[9] This is the same way eBay constructs its Feedback Score utilizing all past auctions. Because eBay weights the feedback equally among all past auctions, regardless of the transaction value, the product category or the role of the feedback recipient, I denote it as the "universal" reputation.[10] I construct a second measure, *gmailscore*, in a similar fashion except that the cumulative sales volume of Gmail invitations is counted instead of the feedback score. This measure is denoted as the "product-specific" dimension of reputation, or Gmail "specialty" reputation, because it explicitly describes the evolution of reputation formed in the marketplace of Gmail invitations alone. In essence, the *gmailscore* measures the leadership status and market share of the seller.

[9] There is a slight difference between the computed Feedback Score and the one reported by eBay because eBay users may elect to keep their entire feedback profile private. The buyers who kept their profile private have their usernames marked as "private" on comments left for other users. While outsiders cannot tell apart all users with private profile, eBay certainly can. The difference is negligible though as there are only 880 comments without an identifiable user name among 549,835 comments in total submitted for 5,445 sellers in this dataset prior to the last day of the sample.

[10] Jin and Kato (2006) term the eBay feedback score as "universal ratings" for similar reasons.

To test the reputation effect on the probability of sale, I run a logit regression

$$\Pr(sale_i = 1|X_i) = G(X_i'\alpha) + \varepsilon_i, \quad (1)$$

where $sale_i$ is an indicator for the success of auction i, X_i is the set of explanatory variables, the coefficients vector α measures the effect on the probability of sale, $G(\cdot)$ is the logistic cumulative density function and ε_i is the residual. An auction is considered successful if the buyer paid the seller the settlement price within the required 90-day period.

In addition to the reputation measures, the set of explanatory variables also includes a squared term for each reputation measure, a market-wide price factor (the hourly price index *meanprice*) and other characteristics such as the seller's age, a geographical location indicator, auction features such as having a reserve price, among other things. While the total number of bids submitted for each auction clearly affects auction outcomes, it is not included as part of the regressors in this study because Bajari and Hortaçsu (2003) convincingly show that the number of bids is an endogenous decision for bidders. For the same reason, Lucking-Reiley et al. (2007) also exclude it as a regressor.

The expectation here is that reputation measures have positive estimated coefficients in order to be consistent with theoretical predictions (see Klein and Leffler, 1981; Shapiro, 1983; Allen, 1984; and Houser and Wooders, 2006). The inclusion of a squared term for the reputation measure is for the detection of non-linearity in reputation effects. Specifically, the famed "Matthew Effect" was coined by Merton (1968) to describe how eminent scientists often get more credit than lesser known researchers. If the already reputed sellers are able to continue accumulating reputation at a lower cost than sellers who just started out the reputation-building process, then the marginal effect of reputation would be declining. Alternatively speaking, the implicit threat of a negative comment carries less weight with the well established sellers than those just starting out. So a negative coefficient for the squared reputation measure would be consistent with the Matthew Effect.

Note that in this and future regression designs I control for the clustered auction items that were closed within the same hour and posted by the same seller. These clustered items are considered correlated observations and thus I use robust standard errors, adjusting for heteroskedasticity and correlation within each cluster, to compute the test statistics.

Resnick et al. (2006) raise an important issue that many empirical studies on eBay fail to adequately control for seller skills such as presenting the auction items in an attractive manner or providing better answers to inquiries. Therefore, the effect of the omitted variables can be mistakenly attributed to seller reputation.

There is no easy way to address unobserved seller characteristics such as their skills. While Resnick et al. (2006) cleverly get around the problem by studying the effects of the same seller peddling under different seller identifications, the vast majority of study subjects in the literature cannot afford the luxury of running controlled experiments.[11] Fortunately, the omitted variable bias is already somewhat mitigated in this sample. The study subject here, Gmail invitations, is both intangible and highly homogeneous, unlike physical and durable goods that make it a challenge for the seller to convey the quality and condition of the subject to the buyer in a reliable way. The seller characteristics such as experience and skill potentially carry more weight when handling complex items than homogeneous product such as Gmail invitations. To the extent that the seller experience matters in this marketplace, I employ the *sellerage* variable (defined as the number of years the seller has been an eBay member as of auction close) as one of the explanatory variables, in addition to the *gmailscore* variable that is designed to capture the leadership status and market share of the seller.

Despite the importance of addressing this omitted variable problem, there exists no standard way in the literature to measure seller skills. Melnik and Alm (2002) and Cabral and Hortaçsu (2004) find that as a proxy for such skills, the inclusion of scanned picture is not significant in affecting the transaction prices. In the context of Gmail invitations, which are simply web links, the inclusion of pictures is likely less relevant. My conjecture is that seller skills should have limited role in this setting of simple and homogeneous product. Furthermore, a casual inspection of the actual listings of Gmail invitations reveals that many sellers simply copied the product features page from Google concerning its Gmail service. In other words, to a large extent, not only is the product itself highly standardized in this setting, but so are the auction listings.

To explicitly measure and control for seller skills, I carry out an exercise of text-mining the titles of all auctions in this sample. The idea is that given the strong competition among sellers in this sample one may exert extra effort to make the auction title stand out, since the auction title provides the primary input for buyers to form the first impression prior to submitting any bid(s). Controlling for heterogeneity in auction titles is important because both the product and the product description are already highly standardized in this context. Moreover, there is little to prevent sellers from copying each other on titles, product descriptions, or both. Sellers can potentially improve their skills over time by learning from their successful competitors and posting auctions with increasingly more effective titles. Therefore, the effectiveness of the auction titles becomes a very relevant proxy for seller skills, and can work better than a time-invariant proxy.

Specifically, I text-mine each auction title to determine whether the seller promoted the auction in any of the following six categories: (1) product condition, (2) product feature, (3) product price, (4) seller persuasiveness, (5) seller responsiveness, and (6) seller trustworthiness. By counting the total number of categories of promotion within each title, I use the resulting *titlescore* to measure seller skills. For example, the auction title "1 google gmail 1GB space invitation, NR, fast delivery" has a *titlescore* of 3 since the seller stresses the large storage space of the Gmail account (category 2), indicates the lack of a reserve price for the auction via the shorthand "NR" for "no reserve" (category 3) and promises "fast delivery" (category 5). As a proxy for seller skills of listing auction

[11] Resnick et al. (2006) have a useful discussion about remaining challenges even this controlled experiment faces.

items, the *titlescore* variable is expected to carry the same sign as reputation effects, i.e., the *titlescore* should positively influence the probability of sale and the buyer's willingness to pay.

In a first test for reputation effects on transaction prices, I run an OLS regression using only successful auctions

$$unitprice_i = X_i'\beta + \eta_i, \tag{2}$$

where $unitprice_i$ is the settlement price per unit of Gmail invitation for auction i, adjusting for shipping costs, β is the vector of coefficients, η_i is the residual and $i \in \{sale_i = 1\}$. Note that studying the reputation effect on transaction prices using only successful auctions leads to truncation bias because failed auctions also contain information on the seller's reputation. However, given the fairly high success rate in this sample (nearly 0.90 on average), the scope for truncation bias is limited even if only the successful auctions are used.

In order to mitigate the truncation bias, it is useful to work out some way of incorporating the failed auctions to assess its effect on the transaction price. Specifically, I run an interval regression in the spirit of Stewart (1983)

$$price_i = X_i'\gamma + \nu_i, \tag{3}$$

where γ is the vector of coefficients and ν_i is the residual. In the case of a successful auction $i \in \{sale_i = 1\}$, the dependent variable is the actual settlement price (*unitprice*). The dependent variable in the case of failed auctions is more complicated because there are two types of failed auctions. The first type of failed auctions is one that attracted some bids $i \in \{sale_i = 0, numbids > 0\}$. For this case, the dependent variable is set as the highest bid submitted (*highbid*) that failed to meet the reserve price. The second type of failed auctions is one without any bids $i \in \{sale_i = 0, numbids = 0\}$. In this case, I specify a reasonable price range $(pricelow_i, pricehigh_i)$ so as to compute the conditional expectation of the buyer's valuation and use it as the dependent variable.

Here is how the valuation bounds are set. Given the availability of an hourly price index *meanprice* as a proxy for the fundamental value, I take advantage of the predicted probability of sale from the logit regression to compute the implied price (*imprice*) as

$$imprice \equiv \widehat{\Pr}(sale_i = 1|X_i) * meanprice. \tag{4}$$

For auctions that failed to attract even a single bid, it is obvious that the required minimum bid *startprice* was not reached. Hence, the upper bound of the true price has to be lower than *startprice*. Although it is simple to set the price boundaries as $(0, startprice)$ for these auctions, the boundaries can be further tightened. The following example demonstrates why using *startprice* alone in a censored-normal model may be insufficient. Suppose the true valuation of the highest bidder was \$10, and two auctions failed with different minimum bids set by the seller at \$12 versus \$100. Using the exceptionally high *startprice* of \$100 as the cutoff in the regression introduces bias that could have been mitigated so long as we were willing to consider a reasonable range for the unobservable true price.

To make the boundaries tighter, I assume that buyers had decided not to submit any bid higher than the implied price for such auctions. Therefore, we have

$$pricelow_i \equiv 0, pricehigh_i \equiv \min(startprice_i, imprice), \tag{5}$$

where $i \in \{sale_i = 0; numbids = 0\}$.

For simplicity, I focus on the coefficients vector γ itself when interpreting the results because the marginal effect on the price requires additional adjustment. Due to the lack of a better term, I call the coefficients inside γ the impact on the "implied buyer's valuation" or the inducement on the "buyer's willingness to pay".

Here are the potential methodological improvements in this paper. Compared to a Tobit model, the interval regression design avoids the pileup of a fixed cutoff point which violates the underlying assumption of normality. Compared to a censored-normal model using minimum bids as the censor point, my approach makes adjustments for some auctions whose minimum bids were set at an unreasonably high level and leads to a tighter price range. The core benefit of using interval regression is to take failed auctions into consideration when studying the net effect of the explanatory variables on the implied buyer's valuation. For example, auctions with a reserve price and a high minimum bid may indeed result in a high price conditional on a successful sale, but the reserve feature and the high minimum bid may also hinder the participation of bidders and unambiguously lower the probability of sale. The net effect of the reserve price or a high minimum bid can be negative on the transaction price. If reputation matters in the way predicted by theory, I expect to find a positive reputation effect on the transaction price, even after correcting for truncation bias.

3 Data

3.1 Data Collection

The data sample in this paper covers the nearly-exhaustive history of eBay auction of Gmail invitations between April 29, 2004 and July 29, 2004. The data extraction involves two different procedures for the two subsamples separated by June 10, 2004. After June 10, 2004, the set of auctions related to Gmail invitations were identified through the eBay search results with one of two keywords – "Gmail invitation" or "Gmail invite". This technique did not work for auctions that were closed prior to June 10, 2004, because I started searching for such auctions on June 24, 2004, and the search engine at eBay does not return auctions that are older than two weeks. Therefore, I rely on a back-filtering procedure to identify the relevant auctions prior to June 10, 2004. The back-filtering procedure works under the assumption that at least one party involved in the early auctions of Gmail invitations would participate in at least one auction of Gmail invitations after

June 10, 2004. In this case, conducting an extensive search among all auctions in the feedback profile for the comprehensive set of buyers and sellers who engaged in such auctions in the later subsample reveals the qualifying auctions in the first subsample.

All the auctions uncovered thus far go through a second layer of screening. I impose a set of 12 filter types and 195 strings to ensure that the subject of each auction consists of only one or more Gmail invitations, and no other product. I also monitor the payment status of the successful auctions and my sample excludes any auction that was not paid within 90 days of the auction closure. This is done to purge auctions whose winners submitted a very high bid but never intended to pay. Given that the auction details are available on eBay through the auction links in users' feedback profile for only 90 days, I chose to collect data for a three-month period since the inception date of this marketplace.

The data collection procedure above yielded 55,094 auctions for the full sample. The back-filtering process produced 2,984 auctions for the subsample prior to June 10, 2004. It is useful to compare the number of auctions reported by the news media to that in my sample. CNET News.com broke the story that Gmail invitations were being auctioned off on eBay (e.g. Kawamoto, 2004). At the time of writing that news report around 11:51am PDT on April 30, 2004, Kawamoto noted 42 such items that were listed on eBay. In the dataset I constructed, there are exactly 42 eBay auctions of Gmail invitation prior to that time. This is corroborating evidence for the success of the back-filtering process.

3.2 Summary Statistics

Table 1 presents some summary statistics about this sample, and the popularity of Gmail invitations is supported by the wide participation of many eBay users with different demographics. During this three-month period, 5,454 sellers from 42 countries participated in the trading of Gmail invitations in eBay, and 30,697 buyers from 62 countries collectively bought 63,378 Gmail invitations for a total value of $393,027.[12] About 71% of the buyers purchased only one Gmail invitation, and the full-sample average is two Gmail invitations per buyer. A Gmail invitation costs $7.29 when averaging the unit price across all auctions sold. The vast majority of sellers were from United States (4,416), Canada (430) and United Kingdom (300), and the geographical allocation among buyers was similarly dominated by these three countries. About 7% of the sellers were not able to sell any Gmail invitations successfully, 74% of the sellers sold between one and ten Gmail invitations, and 18% of the sellers sold between eleven and 100 Gmail invitations during this period.

Some of the best sellers in this sample favored the approach of listing only one Gmail invitation per auction whereas others favored the wholesale fashion. The best seller (username: gimmeadollar) almost always posted one Gmail invitation per auction, and commanded a success rate of 0.91. In

[12] For 10,429 buyers, their respective country of origin could not be identified.

contrast, the fifth seller (username: toma13) sold 680 items in only fifteen auctions, with a perfect success rate.

It is clear that some eBay users participated in the auction of Gmail invitations and were able to boost their reputation rather quickly. The accumulation of reputation did not seem very costly and some users were even able to earn a profit while building a reputation. The fourth best seller (username: ericx1001) had improved his/her Feedback Score from 4 to 508 within 21 days, at an estimated cost of $1.39 per unit increase of the Feedback Score. The best seller (username: gimmeadollar) turned out to also be the best buyer in our sample based on the transaction volume. This eBay user bought 501 Gmail invitations at the total cost of $810.80 and sold 2,153 Gmail invitations for $8,762.12. The Feedback Score of this user was boosted from 3,386 to 5,074 within six weeks between June 17, 2004 and July 29, 2004. It is likely that the user "gimmeadollar" initially bought the Gmail invitations, turned those invitations into a farm of actual Gmail accounts, harvested the additional Gmail invitations from Google Inc. using those accounts, and ultimately sold the new invitations at a profit. In any event, it is reasonable to conclude that some very sophisticated eBay users strategically participated in the auction of Gmail invitations.

The majority of auctions was regular auctions without any special features and enjoyed a higher success rate than those with special features. More than 21% of all auctions had an option known as "Buy It Now", which entitles the potential bidders to make the purchase at the "Buy It Now" price specified by the seller and thus end the auction early. The success rate for auctions with a "Buy It Now" option was about 0.81 for the entire sample, or 0.79 in the period after June 10, 2004. About 1% of all auctions belonged to the Dutch auction type, with a success rate of 0.88 for the entire sample and about the same rate for the second half of the sample.[13] Less than 1% of all auctions had a secret reserve price specified by the seller to block the auction from going through if the highest bid fell below the reserve price. The success rate for auctions with reserve prices was considerably lower, about 0.57 for the entire sample or 0.37 in the second half of the sample, probably because potential buyers were discouraged by the unknown reserve prices.

To have a better grasp of the market dynamics for Gmail invitations in this sample, I construct a few daily indices and plot these time series in Figure 1. It is apparent that the total auctions closed, the total auctions sold and the total Gmail invitations sold closely resemble each other, with pair-wise correlations ranging between 0.97 and 0.99. The time series of the total number of bids submitted each day has a slightly lower correlation (about 0.95) with the three series above.

A few noticeable breaks appear in the plots. When the total number of closed auctions went up from 57 auctions on June 7 to 219 auctions on June 8, the average unit price dropped sharply from almost $71 to $38. The total number of closed auctions reached a local maximum of 874 on June 10, and the price fell to $17 on the same day. The increasing trend of auctions listing continued,

[13] Note that the "Dutch" auction on eBay refers to an ascending-bid second-price auction with multiple items. So there are possibly multiple winners for a Dutch auction, whereas a regular eBay auction has only one winner. This is different from the concept in the auction literature, where the Dutch auction is a descending-bid auction.

as did the decline of the average price. Exactly 2,725 auctions closed on June 16 and the average unit price was \$5. The number of closed auctions reached a daily maximum of 4,710 on June 22, when the average unit price also dropped below \$2 for the first time.

Without knowing the full details of when and by how much Google Inc. relaxed its control in releasing invitations, it is hard to pinpoint the precise turn of events. Anecdotal evidence floating around the internet suggests that at some point around June 9, 2004 Google Inc. decided to release ten invitations for each existing Gmail user, instead of the more typical two-to-three invitations per release. On June 10, 2004 Google Inc. again replenished the consumed Gmail invitations for each user to a balance of ten.[14] Consequently, an increasing number of Gmail invitations flooded eBay and significantly reduced the market price. Some eBay sellers even mentioned stories about the above change by Google Inc. in the description of their auction listings and set their "Buy It Now" prices to a level as low as one penny. The number of closed auctions declined steadily after the peak on June 22, 2004 and the daily average unit price for Gmail invitations never reverted back above the \$10 level.

This is a sample of auctions with a fairly high success rate. Over the full sample, the success rate is 0.89. The last panel of Figure 1 plots the daily average success rate for auctions. Note that in the period prior to June 10, 2004, the success rate was perfect. I did not uncover any evidence that suggests this result is spurious. In fact, the daily success rates after June 10, 2004 also are very high. They vary between 0.73 and 0.97, with a mean of 0.91 and a standard deviation of 0.05.

3.3 Content Analysis of Auction Titles

Content analysis is a popular technique in consumer behavior research that converts descriptive information into categorical data. It has been used in a number of studies regarding online transactions. Pavlou and Dimoka (2006) parse portions of feedback comments from buyers to improve the precision of feedback ratings. Ghose (2009) parse portions of buyer comments to infer the product condition. Dimoka and Pavlou (2008) quantify the auction descriptions to examine the adequacy of text, pictures and multimedia tools. In this paper, I parse the auction titles instead to identify seller skills and it appears to have several advantages. As discussed earlier, both the product and the product description are already highly standardized in my sample, so there is limited potential from parsing the auction descriptions. Given the strong competition among sellers, creating an effective title becomes one of the few places that sellers can make their auction listings stand out in this marketplace. Unlike the buyer comments in the seller feedback profile that are largely ignored by potential buyers,[15] the auction titles are the primary input, and sometimes the only input, for

[14] There is no evidence that Google Inc. continued the practice of automatic refilling invitations for all users after June 10, 2004.

[15] Pavlou and Dimoka (2006) provide evidence that buyers rarely view more than 25 comments for each seller. Ghose (2009) also cites Pavlou and Dimoka (2006) in justifying the practice of parsing only portions of the seller feedback profile.

the formation of buyer perception, which in turn should affect the auction outcomes.

To measure the effectiveness of auction titles as a proxy for seller skills, I text-mine each auction title to determine whether the seller promoted the auction in any of the following six categories: (1) product condition, (2) product feature, (3) product price, (4) seller persuasiveness, (5) seller responsiveness, and (6) seller trustworthiness. The filtering process is based on more than 1,100 keywords among 22 subcategories in total that arise from my manual examination of all 8,217 unique titles among 55,094 auctions.[16] For instance, an auction title is considered a fit for the category of promoting product condition if the title mentions any of the following keywords regardless of capitalization: "brand new", "fresh", "fresh and delicious", "freshly squeezed", "neu", "new", "new unused", "new/unused", "shiny new", "unactivated account", "unregistered", "unused", "username not yet selected".

The process of identifying keywords and classifying them into categories and subcategories is somewhat subjective, as would be any content analysis that involves defining categories and training judges who ultimately decipher the content. This step is inevitable, however, because of the ineffectiveness of a totally objective approach like the well-known General Inquirer that compares words against a specific dictionary. The length limitation on the auction titles often forces sellers to use abbreviated words rather than fully spelling them out, and different sellers can use very different ways to abbreviate the same word. Given the global reach of eBay Inc., foreign sellers occasionally use their native language in the auction titles as well. Misspelled words and internet lingo can also pop up in auction titles. One may be surprised to learn that there are 31 keywords uncovered from this sample, all of which describe "free shipping" as a subcategory of category (3) concerning product price.

These and other complications mandate some form of human examination and I have tried to minimize the human involvement to the extent possible to ensure objectivity. Rather than employing human annotators to decipher the content as is done in many studies, I rely on a perl script to conduct the filtering process automatically once the classification of keywords is finalized.

I use six dummy variables, $category1$ through $category6$, to describe the filtering outcomes. The filtering procedure determines whether the title under examination contains one of the keywords under a certain category. If yes, then the dummy variable for the respective category of promotion is assigned a value of 1; otherwise, a zero value is assigned instead. I denote the sum of these six dummy variables by $titlescore$ and use $titlescore$ as a proxy for seller skills.

Table 2 reports the summary statistics of the content analysis. Nearly 71% of all auction titles describe various aspects of product features such as the choice of a custom name, the large storage space that Gmail provides in comparison to its competitors, etc. Sellers promise a quick response to inquiries or quick delivery of product in the titles 23% of the time. The emphasis on attractive prices (in the form of free shipping, no fees, no reserve price, low starting bid or low price) is seen

[16] A copy of the detailed keywords and subcategories used in this study is available upon request.

in close to 18% of all auction titles. Among 17% of the auctions, sellers also hype about the Gmail service, purport it to be rare, or urge buyers to act promptly. Close to 15% of all auctions have titles with self-claimed trustworthiness, drawing attention to an established feedback profile or past sales record, and promising or guaranteeing the authenticity of the product. Given the extreme homogeneity and intangible nature of Gmail invitations, very few sellers portray the auction subject as new in this sample. There are only 538 auctions with a title that describes the Gmail invitation being new, amounting to about 1% of auction titles that promote "product condition."

The distribution of *titlescore* is concentrated among values of 1 and 2. About 47% of auction titles mention information in only one category of promotion, and 35% of them make two categories of promotion. A little more than 9% of the auction titles do not fit in any of these six title categories, carrying a rather plain description of the auction subject. Among the more skillful sellers, about 8% of the titles advertise in three categories, 0.73% of the titles fit four categories and 0.21% of the titles fit five. No seller attempts a title with information on all six categories, partly reflecting the fact that mentioning product condition in this context is not particularly useful.

4 Empirical Results

4.1 Reputation Effects on Probability of Sale

To mitigate the concern that the perfect success rate among auctions in the first subsample may be driven by the back-filtering process at the data collection stage, I focus on the auctions after June 10, 2004 in the current subsection. I run three versions of the design (1), by including both the universal and the product-specific components of reputation together, or leaving out one of them. Table 3 presents the logit regression results in three groups, and a clear pattern emerges concerning the reputation effects. Each reputation measure is positive and statistically significant at the 1% level and the respective squared term for the reputation measure is negative and statistically significant. In other words, the reputation influence on the probability of sale has the anticipated sign consistent with the theoretical prediction. Although the reputation effect being concave is not part of the theoretical prediction, it is nevertheless consistent with the Matthew Effect. In other words, the marginal incentive of building a good reputation is highest at the early stage of the track record and gradually declines over time. These results are robust across all three versions of the design (1) with a pseudo-R^2 around 16% and highly significant Wald-statistics indicating the joint significance of the explanatory variables. The fact that the Gmail specialty reputation withstood the competition of the universal reputation, the more traditional measure of reputation, points to the potential of an omitted variable bias in existing studies that ignore product specificity.

It is interesting to note that when proxied by the *titlescore* seller skills register positively, which is consistent with the prior expectation, but not in a statistically significant way. When the composite *titlescore* is replaced by the individual dummies for all six categories of promotion, there is virtually no change to reputation effects documented here.[17] The title category (4) concerning the seller persuasiveness positively affects the sales probability with statistical significance bordered at the 10% level. Both the title categories (1) and (6) have a negative, and strongly statistically significant, impact on the sales probability. This is evidence that sellers who attach a "new" label to an item that should have been new anyway, or sellers who emphasize the self-claimed trustworthiness, can actually deter bidder participation. The opposing effects of individual components of the *titlescore* contribute to the overall insignificance of *titlescore* with respect to the probability of sale.

To illustrate the economic significance of reputation effects, I show in Table 4 the changes in the predicted probability of sale corresponding to different values for a selected group of explanatory variables. The calculations here are based on the estimated coefficients in the logit design (1) including both dimensions of reputation. All variables except the one under the control are set to their respective subsample mean values when calculating the predicted probability of sale. Whenever the reputation measure is controlled, its squared term is as well.

The first few rows of Table 4 illustrate the influence of reputation on the predicted probability of sale when the seller's reputation improves from the lowest to the next quintile. Improving from the lowest to the next quintile in the universal reputation alone helps raise the predicted probability of sale by about 0.02. Likewise, improving from the lowest to the next quintile along the product-specific dimension of reputation alone boosts probability of sale by 0.03. For sellers improving their reputation measure on both dimensions from the lowest to the next quintile, there is an increase of about 0.05, or 6.2%, in the predicted probability of sale. This result is compelling evidence that both dimensions of reputation have a strongly positive influence on the probability of sale, an effect that is not only statistically significant but also economically significant.

As far as seller skills are concerned, the *titlescore* shows negligible economic impact on the sales probability. The expected probability of sale is virtually identical between sellers who employ a very plain description in the auction titles and those whose auction titles fit into exactly one category of promotion.

In terms of magnitude of impact, the largest change in the predicted probability of sale occurs for the indicator variable whether the seller sets a reserve price. For sellers who set a reserve price on the auction, all other things being equal, the predicted probability of sale falls from 0.90 to 0.35, a drop of more than 60%. This finding reflects the fact that bidders on eBay are extremely reluctant to participate in auctions with a reserve price, and is consistent with the result in Dewan and Hsu (2004). In this sample less than one percent of all auctions had the reserve feature. Because sellers in this marketplace can always return to eBay and re-list the unsold Gmail invitations, they have no incentive to state the reserve price above the true value, according to Milgrom (1997). For sellers who obtained their Gmail invitations directly from Google Inc. free of charge, the true

[17] The results from this alternative specification are untabulated but available from the author upon request.

reservation value should be the listing fee charged by eBay. Given that the listing fee for a low value item such as Gmail invitations is negligibly small and the discouragement of a reserve price to the participation of bidders is so large, most sellers chose not to set a reserve price for Gmail invitations as the costs would outweigh the benefits. Not surprisingly, setting a high minimum bid (at or more than 120% of the prevailing market price) cuts the probability of sale by about 0.10. Moreover, setting the "Buy It Now" option decreases the probability of sale by nearly 0.06 and having the auction close on Sunday increases probability of sale by about 0.06, all else being equal.

4.2 Reputation Effects on Transaction Prices of Successful Auctions

Table 5 presents the ordinary least square regressions using all successful auctions in the full sample. We use three different versions of design (2), by including both the universal and the product-specific components of reputation together, or leaving out either of the two components. The more traditional measure of reputation based on the Feedback Score has a positive and significant coefficient, consistent with the theoretical predictions. Its squared term is negative, showing some evidence in support of the Matthew Effect again. The Gmail specialty reputation loses its edge in this regression design, with estimated coefficients that are insignificantly different from zero, regardless of whether it faces the competition of the universal reputation.

The composite *titlescore* is associated with a positive coefficient that is statistically significant at the 1% level. It reinforces the argument in Resnick et al. (2006) that seller skills should be accounted for; otherwise, the estimated reputation effects can be biased upward. When the *titlescore* is replaced by the dummies for individual categories of promotion, the results for which are again untabulated to conserve space but available from the author upon request, the qualitative pattern of reputation effects and seller skills is unaltered. All the individual title categories enter the regression positively and are significant at the 1% or 5% level with two exceptions: the dummy for auction titles featuring product condition is positive but insignificant at conventional levels, and the dummy for auction titles advertising low price is positive and significant at the 10% level. Neither exception is surprising.

It is worth noting that the estimated coefficient for the market price index is 0.84 across all three designs, indicating that successful auctions fetch a price fairly close to the prevailing market price. Auctions with longer display time seem to earn higher prices. This result is statistically significant at the 1% level across all three versions of the design, and this is one of the main results in Lucking-Reiley et al. (2007). I also find that successful auctions with a reserve price fetch higher prices and a high minimum bid would earn the seller a higher price conditional on the auction being sold. While these two results confirm the main findings in Lucking-Reiley et al. (2007), they are counter-intuitive nevertheless because these two features are expected to deter bidder entry. Note that Dewan and Hsu (2004) support the finding in this sample that a reserve price dramatically lowers the probability of sale and boosts the ending price conditional on a successful auction.

The results are generally robust across different specifications with R^2 around 88% and highly significant F-statistics indicating the joint significance of the explanatory variables. The high R^2 should not be over-interpreted because it is very important to include a benchmark price in this regression, and the market price index (i.e., average unit price in the preceding hour) is a dominant explanatory variable. I do not find evidence, however, suggesting that the high R^2 arises from a spurious relationship between the auction price and the average unit price in the preceding hour.[18]

4.3 Reputation Effects on Transaction Prices of All Auctions

Since using only the successful auctions potentially leads to truncation bias, the ordinary least square regression results in Table 5 should be interpreted cautiously. The interval regression design (3) is intended to fix the truncation bias by using the implied price from the logit regression (1) so as to deliver a tighter bound on the true price. The results for the interval regressions using all available data, including the failed auctions, are presented in Table 6, again with three versions of regression designs changing the combination of the two dimensions of reputation. The results are again robust across the three versions with very highly significant Wald-statistics indicating the joint significance of the explanatory variables used.

The universal reputation in the entire sample retains the same qualitative property as in the regression results using only successful auctions. That is, this reputation measure has a positive and significant estimate that is consistent with the theoretical prediction, and its squared term is negative and significant, supporting the Matthew Effect. In terms of economic significance, the improvement of the seller's eBay feedback score from the lowest to the next quintile induces a 27 cent increase in the buyer's willingness to pay the seller, when both dimensions of reputation are accounted for. Given the sample mean implied price at \$6.32, based on the unit price for successful auctions and the expected price for failed auctions conditional on the implied price range, the universal reputation effect on the implied buyer's valuation is about 4.2% for a seller whose eBay feedback score moves from the lowest to the next quintile.

One remarkable feature of the results is that the product-specific dimension of reputation gains importance after adjusting for failed auctions. In particular, the estimated coefficient for the Gmail specialty reputation is positive and significant even when the universal reputation is also included. From the perspective of economic significance, the improvement of the seller's *gmailscore* from the lowest to the next quintile induces a 12 cent increase in the buyer's willingness to pay, or about 1.9%. Sellers who improve both dimensions of reputation from the lowest to the next quintile would have an increase of 39 cents in the implied buyer's valuation, or a hike of about 6.1%.

Like the results based on successful auctions only, seller skills as measured by the composite

[18] I find that using the average unit prices of auctions closed in the previous three hours lead to only a small reduction in R^2 and no qualitative change in the estimated coefficients for the explanatory variables. Using a new dependent variable as the auction price scaled by the average unit prices in the previous hour leads to a lower R^2, but again there is no qualitative change in the reputation effects.

titlescore positively affect the buyers' willingness to pay. The effect is statistically significant at the 1% level across three designs. Compared to sellers who use plain titles, sellers whose titles fit exactly one category of promotion would fetch 16 cents more, about 2.6% of the sample mean implied price. In untabulated results, I also find that when replacing the *titlescore* by the dummy variables for six title categories, only titles promoting product features, seller responsiveness and seller trustworthiness boost price in a way that is statistically significant at the 1% level. The reputation effects are robust to this alternative design.

The qualitative nature for most control variables does not change in the interval regression using the entire sample, compared to the regression using only the successful auctions (see Table 5). There are two control variables that switched signs. When the seller sets a reserve price on the auction, the probability of sale is undercut significantly from 0.90 to 0.35 such that the implied buyer's valuation drops by 46 cents. But this effect is not statistically significant in this sample, perhaps because few auctions (0.79% of all auctions) in this sample have specified the reserve price. The negative sign for auctions with a reserve price is nevertheless consistent with the finding of Katkar and Reiley (2006). In a controlled experiment, they show that sellers are worse off when setting reserve prices on otherwise identical auctions. Relative to the regression result on successful auctions, the impact of the required minimum bid on the implied buyer's valuation flips its sign in a statistically significant sense, but its economic significance is minimal as it depresses the transaction price by merely one basis point relative to the minimum bid. The near-zero influence of the required minimum bid echoes the argument made by Lucking-Reiley et al. (2007) that the level of minimum bid should not matter in auctions with more than one bidder. Indeed, the auction of Gmail invitations had an average of 4.47 bids in this sample. It is worth stressing that in the current design the signs for these two control variables flipped in favor of the intuition that reserve prices and minimum bids deter bidder participation. The flip of signs is not unique to this sample as Dewan and Hsu (2004) report exactly the same pattern for the reserve price. Perhaps the sign change after controlling for failed auctions highlights the importance of addressing the truncation bias.[19]

4.4 Test for Declining Price Anomaly

Ashenfelter (1989) identified a "declining price anomaly" in auctions of identical wines. It refers to the finding that the price of identical auctions tends to fall over time, a situation inconsistent with the predicted behavior of risk-neutral bidders. Ashenfelter and Genesove (1992) provide further evidence of this anomaly in real-estate auctions and Van den Berg et al. (2001) show its presence

[19] Dewan and Hsu (2004) study the reputation effects after controlling for failed auctions with a Tobit model. Their sample consists of 9,981 auctions with a success rate of .64. Lucking-Reiley et al. (2007) use a censored-normal approach to handle auctions where the reserve prices were not met. Their sample consists of 461 auctions with a success rate of .62. Lucking-Reiley et al. (2007) note that the book value series comes from surveys of dealers' list prices, which may or may not reflect actual transactional prices. As of this writing, Dimoka and Pavlou (2008) study only those successful auctions of used cars (with a success rate of about 0.20) and do not address the truncation bias.

in rose auctions. McAfee and Vincent (1993) empirically verify the existence of such an anomaly in wine auctions and theoretically justify such a phenomenon as the rational behavior of risk-averse bidders. Ginsburgh (1998) offers a different view that this anomaly may be caused by absentee bidders who use non-optimal bidding strategies. Since this paper studies a market of homogeneous goods, it is feasible to test whether the "declining price anomaly" is present here.

Specifically, I select a group of successful auctions that were posted by the same seller and closed within the same hour and run the following regression,

$$unitprice_i = X_i'\delta + \xi_i, \tag{6}$$

where the dependent variable $unitprice_i$ is the settlement price of a Gmail invitation for auction i, adjusting for shipping costs, δ is the coefficients vector and ξ_i is the residual. The explanatory variables set X_i consists of all the explanatory variables in previous analysis, in addition to the sequence number of these auctions ordered by the closing time. The sequence number takes a value between one (for the auction with the earliest closure) and the total number of successful auctions that were posted by the same seller and closed within the same hour.

Based upon the total number of successful auctions that were posted by the same seller and closed within the same hour, I classify the sample into groups of "identical" auctions that have an almost identical set of explanatory variables except the sequence number. A larger number of successful auctions that were posted by the same seller and closed within the same hour indicate a better approximation of "identical" auctions. I run the regression design (6) individually for the top groups and also run this regression for the pooled data. A statistically significant and negative coefficient on the sequence number is interpreted as evidence for the presence of a "declining price anomaly". Note that many of the explanatory variables would drop out of the regression due to the lack of variation in these variables within the selected group.

Table 7 presents the regression results for the top eleven groups of "identical" auctions. For instance, the seller "zuckas" successfully sold 89 auctions within one particular hour. Those auctions were posted by the same seller and completed in a manner of rapid fire with more than one successful auction per minute. There should be no significant changes in the auction environment during this period so they can be considered as "identical". When I use the unit price of Gmail invitations for these 89 auctions as the dependent variable, I find that the estimated coefficient for the sequence number is positive (0.0092) and significant at the 5% level. Therefore, there is evidence against the "declining price anomaly" based on this particular group of "identical" auctions. Moving down to the 76 successful auctions by the seller "newyorkdiamonds" within one hour, there appears a positive, yet insignificant, coefficient for the sequence number. This result, again, does not support the "declining price anomaly".

Similarly, I run the same regression design for another nine groups of "identical" auctions, and the evidence regarding the "declining price anomaly" is mixed. Overall, there are six positive coefficients and five negative coefficients on the sequence number. Two of the positive coefficients are statistically significant while three of the negative coefficients are statistically significant. When pooling these eleven groups together, the regression result turns out a negative, yet insignificant, coefficient on the sequence number. Therefore, the conclusion is that in this sample there is not strong evidence in favor of the "declining price anomaly."

5 Conclusion

In this paper, I utilize a unique collection of auctions on eBay to study the influence of seller reputation on auction outcomes. Departing from the "universal" reputation in eBay studies which fails to differentiate the track record in different product markets, I introduce a "product-specific" reputation that accounts for the specificity of product markets where the reputation is established.

By studying the reputation effects on the probability of sale and on the transaction price together, I find compelling evidence in support of the positive relationships predicted by theory. Effects of both the universal and the product-specific reputation are highly economically significant after adjusting for truncation bias from failed auctions and controlling for seller skills. Sellers who improve both measures of reputation from the lowest to the next quintile experience a 6.2% higher probability of sale and a 6.1% hike in the implied buyer's valuation. This finding is important for empirical studies of reputation effects because the failure to account for the product-specific dimension of reputation amounts to an omitted variable bias.

This paper explicitly measures seller skills by quantifying the effectiveness of all auction titles. Specifically, I text-mine each auction title to determine whether the seller promoted the auction in any of six broad categories, and use the total number of categories of promotion within each title as a proxy for seller skills. The resulting composite measure has only marginal impact on the probability of sale, but positively affects the buyer's willingness to pay even after adjusting for truncation bias. The positive relationship between seller skills and price is both statistically and economically significant. This paper makes an important contribution to the extant literature by directly addressing the concern in Resnick et al. (2006) that many empirical studies on eBay suffer from an omitted variable bias due to lack of control for seller skills. This paper's method of measuring seller skills by quantifying the effectiveness of auction titles can be easily implemented in other empirical studies.

Finally, this paper enriches the literature by showing that reputation matters even in the context of homogeneous goods with non-enforceable contracts. The reputation effects demonstrated in this paper serve as a conservative estimate because counterparties in a more complex market have a stronger need for using reputation as a quality signal for unobservable characteristics. Namely, a good reputation should be valued even more in markets involving more complex products.

There is also some evidence of concavity on the reputation effects, a finding consistent with the

Matthew Effect coined by Merton (1968). While the sample of auctions in this paper provides a natural environment for studying the "price declining anomaly" first documented by Ashenfelter (1989), I do not find strong evidence in support of such an anomaly.

In addition to being well suited for studying reputation effects, the dataset compiled in this paper provides a fertile ground for future studies of auction designs. For example, studying the transaction profile of buyers and sellers in this dataset can help shed some light on the strategic interactions among them. By making reasonable assumptions regarding the bidder's preference, one can empirically verify the theoretical predictions on how sellers should set the auction features so as to maximize their expected revenue, and on how reputation plays out in the decision of bidder participation. I leave these and other interesting topics for future research.

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Table 1
Summary Statistics

This table provides summary statistics for auctions of Gmail invitations on eBay between April 29, 2004 and July 29, 2004. All the auctions were sold successfully before June 10, 2004. The auctions on and after June 10, 2004, also denoted as "2nd half", contain both successful and failed auctions. The Unit Price is computed as the sum of the settlement price and shipping costs divided by the auction quantity. All prices in the original currency were converted into US Dollars using the daily exchange rate from Datastream. For weekends, the exchange rate on the preceding Friday was used.

Number of Auctions Closed	55,094
Number of Auctions Sold	48,903
Number of Items Sold	63,378
Number of Sellers	5,454
Number of Countries of Seller Origin	42
Number of Buyers	30,697
Number of Countries of Buyer Origin	62
Number of Currencies Involved	6
Number of Auctions Closed (2nd Half)	52,110
Number of Auctions Sold (2nd Half)	45,919

Number of Sellers with x Items/Auctions	Sold	Closed
x equal 0	395	0
x less than or equal to 2	2,495	2,547
x less than or equal to 5	3,627	3,730
x less than or equal to 10	4,371	4,483
x less than or equal to 20	4,869	4,957
x less than or equal to 50	5,239	5,280
x less than or equal to 100	5,365	5,389
x less than or equal to 200	5,422	5,431
x less than or equal to 400	5,439	5,447

Top Five Sellers by Items Sold	Rank	Sold
gimmeadollar	1	2,153
sohonestman	2	1,678
tshirtfreak.com	3	1,620
*ericx*1001	4	770
*toma*13	5	680

Top Five Sellers by Auctions Closed	Rank	Closed
gimmeadollar	1	2,166
sohonestman	2	1,510
tshirtfreak.com	3	850
*ericx*1001	4	806
newyorkdiamonds	5	684

Auctions with Special Features	Closed	Sold
Buy It Now	11,814	9,609
Dutch	557	492
Reserve	436	247

Auctions with Special Features (2nd Half)	Closed	Sold
Buy It Now	10,639	8,434
Dutch	545	480
Reserve	301	112

Selected Statistics for Unit Price in USD			
Minimum	0.01	Mean	7.29
25% percentile	1.99	Standard Deviation	12.82
Median	3.75	Skewness	4.62
75% percentile	6.50	Kurtosis	26.16
Max	200.00		

Table 2
Content Analysis of Auction Titles

This table presents the summary statistics from a content analysis of auction titles. I text-mined each auction title to determine whether the seller promoted the auction in any of the following six categories: (1) product condition, (2) product feature, (3) product price, (4) seller persuasiveness, (5) seller responsiveness, and (6) seller trustworthiness. By counting the total number of categories of promotion within each title, I use the resulting *titlescore* to measure seller skills. See Section 3.3 for details of the filtering procedure. There are 55,094 auctions of Gmail invitations on eBay between April 29, 2004 and July 29, 2004. The number of auctions with titles fitting in each category is documented along with its fraction among all auctions. Also reported are the number of auctions with different values of *titlescore* and their respective fractions among all auctions.

Title Categories	Auctions	Fraction
product condition	538	0.98%
product feature	38,867	70.55%
product price	9,854	17.89%
seller persuasiveness	9,532	17.30%
seller responsiveness	12,836	23.30%
seller trustworthiness	8,143	14.78%

titlescore	Auctions	Fraction
0	5,108	9.27%
1	25,710	46.67%
2	19,408	35.23%
3	4,346	7.89%
4	404	0.73%
5	118	0.21%
6	0	0.00%

Table 3
Reputation Effects on Probability of Sale

This table presents the results of the logit regression on the outcome of all auctions in the second subsample between June 10 and July 29, 2004. The reputation measures *ebayscore* and *gmailscore* are defined in Section 2.4. The squared terms for these variables carry a suffix "2". I text-mined each auction title to determine whether the seller promoted the auction in any of the following six categories: (1) product condition, (2) product feature, (3) product price, (4) seller persuasiveness, (5) seller responsiveness, and (6) seller trustworthiness. By counting the total number of categories of promotion within each title, I use the resulting *titlescore* to measure seller skills. See Section 3.3 for details of the filtering procedure. The market price index and the number of auctions closed in the preceding hour are denoted by *meanprice* and *numclosed*, respectively. The *sellerage* refers to years that the seller has been an eBay member. The auction duration in hours is denoted by *durhour*. The variable *dayid* carries the numerical sequence of the ending day. Also included as explanatory variables are some indicators, *buyitnow* for auctions with a Buy It Now feature, *reserve* for auctions with a reserve price, *startprice* for auctions with a required minimum price, *highprice* for auctions with a required minimum price exceeding 120% of the prevailing market price index, *uscanuk* for sellers from U.S., Canada or U.K., *afternoon* for auctions with ending time in [12:00:00, 18:00:00), *evening* for auctions with ending time in [18:00:00, 23:59:59], and *tues2thur* for auctions ended between Tuesday and Thursday. The indicator variables, *friday*, *saturday* and *sunday*, are defined similarly. The estimated coefficients $\widehat{\alpha}$ are reported along with t-stats based on robust standard errors. Also reported are the Wald-stats and the pseudo-R^2. Statistical significance at the 1%, 5% and 10% level is denoted by ***, ** and *, respectively.

	$\widehat{\alpha}$	t-stat		$\widehat{\alpha}$	t-stat		$\widehat{\alpha}$	t-stat	
ebayscore2	−0.1037	−3.72	***				−0.0829	−2.52	**
ebayscore	0.3697	4.09	***				0.2933	3.05	***
gmailscore2				−0.1263	−4.39	***	−0.1039	−2.81	***
gmailscore				0.5022	4.50	***	0.4386	3.65	***
titlescore	0.0344	0.74		0.0185	0.36		0.0255	0.54	
meanprice	0.1144	6.17	***	0.1163	6.34	***	0.1188	6.46	***
numclosed	−0.0039	−6.98	***	−0.0040	−6.45	***	−0.0040	−7.06	***
buyitnow	−0.5204	−5.61	***	−0.5141	−5.05	***	−0.5590	−5.72	***
reserve	−2.8865	−9.78	***	−2.7894	−9.52	***	−2.7834	−9.12	***
startprice	−0.1122	−9.04	***	−0.1049	−8.51	***	−0.1061	−8.47	***
highprice	−0.8161	−7.19	***	−0.8404	−7.27	***	−0.8250	−7.26	***
sellerage	−0.0046	−0.14		−0.0091	−0.32		−0.0029	−0.08	
uscanuk	0.1624	1.10		0.2158	1.57		0.1493	0.99	
durhour	−0.0052	−5.01	***	−0.0050	−4.36	***	−0.0046	−4.05	***
dayid	0.0078	1.77	*	0.0087	1.93	*	0.0086	1.92	*
afternoon	−0.0836	−0.81		−0.0938	−0.81		−0.0844	−0.79	
evening	−0.1612	−1.78	*	−0.1644	−1.81	*	−0.1690	−1.87	*
tues2thur	0.0302	0.25		0.0496	0.37		0.0303	0.25	
friday	0.2081	1.37		0.2153	1.30		0.1943	1.25	
saturday	−0.0363	−0.23		−0.0137	−0.08		−0.0439	−0.27	
sunday	0.8198	4.86	***	0.8096	4.61	***	0.8030	4.69	***
constant	1.7886	3.85	***	1.5449	3.22	***	1.4969	3.16	***
	pseudo-R^2	$\chi^2(19)$		pseudo-R^2	$\chi^2(19)$		pseudo-R^2	$\chi^2(21)$	
	0.1604	1208.92	***	0.1617	1225.62	***	0.1639	1256.83	***

Table 4
Changes in Predicted Probability of Sale

This table presents the changes in the predicted probability of sale for a selected set of control variables, using the logit regression results with both dimensions of reputation (see the third group of coefficients in Table 3). All variables other than the one(s) under control were set to the sample mean value when calculating the predicted probability of sale. Note that whenever *ebayscore* is controlled for, so is its squared term $ebayscore2$. This practice of joint treatment is denoted by $ebayscore(2)$. A similar treatment is applied on *gmailscore*. When the treatment variable $x(i)$ takes value 1, the predicted probability of sale is listed under the column label "$x(i) = 1$". When the treatment variable takes value 0, the predicted probability of sale is listed under the column label "$x(i) = 0$." The last column of the table presents the change in the predicted probability of sale as a result of applying the treatment.

$x(i)$	$x(i) = 1$	$x(i) = 0$	change
$ebaysore(2)$	0.9071	0.8878	0.0193
$gmailscore(2)$	0.9039	0.8706	0.0333
$ebayscore(2); gmailscore(2)$	0.9142	0.8607	0.0535
$titlescore$	0.8949	0.8925	0.0024
$buyitnow$	0.8466	0.9061	−0.0595
$reserve$	0.3511	0.8975	−0.5463
$highprice$	0.8040	0.9035	−0.0995
$uscanuk$	0.8971	0.8825	0.0146
$afternoon$	0.8905	0.8984	−0.0080
$evening$	0.8836	0.8999	−0.0163
$tues2thur$	0.8974	0.8946	0.0028
$friday$	0.9110	0.8940	0.0171
$saturday$	0.8923	0.8964	−0.0041
$sunday$	0.9466	0.8881	0.0585

Table 5
Reputation Effects on Sale Prices of Successful Auctions

This table presents the ordinary least square regression results on the price of a Gmail invitation using all successful auctions in the full sample period. The reputation measures *ebayscore* and *gmailscore* are defined in Section 2.4. The squared terms for these variables carry a suffix "2". I text-mined each auction title to determine whether the seller promoted the auction in any of the following six categories: (1) product condition, (2) product feature, (3) product price, (4) seller persuasiveness, (5) seller responsiveness, and (6) seller trustworthiness. By counting the total number of categories of promotion within each title, I use the resulting *titlescore* to measure seller skills. See Section 3.3 for details of the filtering procedure. The market price index and the number of auctions closed in the preceding hour are denoted by *meanprice* and *numclosed*, respectively. The *sellerage* refers to years that the seller has been an eBay member. The auction duration in hours is denoted by *durhour*. The variable *dayid* carries the numerical sequence of the ending day. Also included as explanatory variables are some indicators, *buyitnow* for auctions with a Buy It Now feature, *dutch* for dutch auctions, *reserve* for auctions with a reserve price, *startprice* for auctions with a required minimum price, *highprice* for auctions with a required minimum price exceeding 120% of the prevailing market price index, *uscanuk* for sellers from U.S., Canada or U.K., *afternoon* for auctions with ending time in [12:00:00, 18:00:00), *evening* for auctions with ending time in [18:00:00, 23:59:59], and *tues2thur* for auctions ended between Tuesday and Thursday. The indicator variables, *friday*, *saturday* and *sunday*, are defined similarly. The estimated coefficients $\widehat{\beta}$ are reported along with t-stats based on robust standard errors. Also reported are the F-stats and the R^2. Statistical significance at the 1%, 5% and 10% level is denoted by ***, ** and *, respectively.

	$\widehat{\beta}$	t-stat		$\widehat{\beta}$	t-stat		$\widehat{\beta}$	t-stat	
ebayscore2	−0.0523	−3.25	***				−0.0570	−3.43	***
ebayscore	0.3085	4.25	***				0.3268	4.33	***
gmailscore2				0.0221	1.42		0.0191	1.14	
gmailscore				−0.0502	−0.73		−0.0857	−1.20	
titlescore	0.1749	6.07	***	0.1802	6.24	***	0.1764	6.10	***
meanprice	0.8416	55.00	***	0.8414	54.92	***	0.8414	54.86	***
numclosed	−0.0040	−8.16	***	−0.0039	−8.13	***	−0.0039	−8.15	***
buyitnow	−2.6212	−28.84	***	−2.5918	−28.55	***	−2.6205	−28.77	***
dutch	−0.6439	−4.54	***	−0.5943	−4.18	***	−0.6573	−4.59	***
reserve	2.0651	2.53	**	2.0158	2.47	**	2.0492	2.51	**
startprice	0.1891	11.67	***	0.1886	11.64	***	0.1890	11.67	***
highprice	4.4955	40.11	***	4.5182	40.10	***	4.4942	40.07	***
sellerage	−0.0103	−0.66		0.0130	0.88		−0.0109	−0.69	
uscanuk	0.1032	1.39		0.1008	1.37		0.1005	1.35	
durhour	0.0106	9.74	***	0.0092	8.59	***	0.0104	9.46	***
dayid	−0.0341	−8.33	***	−0.0336	−8.16	***	−0.0339	−8.24	***
afternoon	0.1406	2.27	**	0.1422	2.30	**	0.1398	2.26	**
evening	−0.0521	−0.82		−0.0477	−0.75		−0.0513	−0.81	
tues2thur	−0.2318	−3.03	***	−0.2285	−2.97	***	−0.2301	−3.01	***
friday	−0.1479	−1.35		−0.1456	−1.32		−0.1433	−1.30	
saturday	−0.3181	−3.23	***	−0.3073	−3.11	***	−0.3149	−3.19	***
sunday	0.0024	0.02		0.0066	0.07		0.0071	0.07	
constant	2.9741	6.69	***	3.1615	7.03	***	3.0124	6.68	***
	R^2	F-stat		R^2	F-stat		R^2	F-stat	
	0.8759	1400.31	***	0.8758	1431.75	***	0.8759	1298.17	***

Table 6
Reputation Effects on Sale Prices of All Auctions

This table presents the results of the interval regression using all auctions in the entire sample period. For successful auctions, the unit price is used as the dependent variable. For failed auctions with some bids, the highest bid price is used as the dependent variable. For failed auctions without any bid, the boundary values of the dependent variable are set according to equations (4) and (5). The reputation measures *ebayscore* and *gmailscore* are defined in Section 2.4. The squared terms for these variables carry a suffix "2". I text-mined each auction title to determine whether the seller promoted the auction in any of the following six categories: (1) product condition, (2) product feature, (3) product price, (4) seller persuasiveness, (5) seller responsiveness, and (6) seller trustworthiness. By counting the total number of categories of promotion within each title, I use the resulting *titlescore* to measure seller skills. See Section 3.3 for details of the filtering procedure. The market price index and the number of auctions closed in the preceding hour are denoted by *meanprice* and *numclosed*, respectively. The *sellerage* refers to years that the seller has been an eBay member. The auction duration in hours is denoted by *durhour*. The variable *dayid* carries the numerical sequence of the ending day. Also included as explanatory variables are some indicators, *buyitnow* for auctions with a Buy It Now feature, *dutch* for dutch auctions, *reserve* for auctions with a reserve price, *startprice* for auctions with a required minimum price, *highprice* for auctions with a required minimum price exceeding 120% of the prevailing market price index, *uscanuk* for sellers from U.S., Canada or U.K., *afternoon* for auctions with ending time in [12:00:00, 18:00:00), *evening* for auctions with ending time in [18:00:00, 23:59:59], and *tues2thur* for auctions ended between Tuesday and Thursday. The indicator variables, *friday*, *saturday* and *sunday*, are defined similarly. The estimated coefficients $\widehat{\gamma}$ are reported along with t-stats based on robust standard errors. Also reported are the Wald-stats. Statistical significance at the 1%, 5% and 10% level is denoted by ***, ** and *, respectively.

	$\widehat{\gamma}$	t-stat		$\widehat{\gamma}$	t-stat		$\widehat{\gamma}$	t-stat	
ebayscore2	−0.0695	−3.97	***				−0.0662	−3.69	***
ebayscore	0.3788	4.97	***				0.3344	4.28	***
gmailscore2				−0.0211	−1.26		−0.0166	−0.91	
gmailscore				0.1857	2.53	**	0.1358	1.80	*
titlescore	0.1718	5.58	***	0.1626	5.21	***	0.1613	5.20	***
meanprice	0.9245	77.57	***	0.9247	77.27	***	0.9249	77.23	***
numclosed	−0.0030	−6.01	***	−0.0031	−6.18	***	−0.0031	−6.26	***
buyitnow	−1.0210	−11.95	***	−0.9750	−11.44	***	−1.0068	−11.71	***
dutch	−0.2985	−1.91	*	−0.2326	−1.48		−0.3102	−1.97	**
reserve	−0.4972	−0.64		−0.4841	−0.62		−0.4551	−0.58	
startprice	−0.0001	−4.51	***	−0.0001	−4.56	***	−0.0001	−4.48	***
highprice	2.1096	17.32	***	2.1302	17.29	***	2.1179	17.33	***
sellerage	−0.0170	−1.04		0.0079	0.50		−0.0095	−0.57	
uscanuk	0.0094	0.12		0.0360	0.48		0.0175	0.23	
durhour	0.0045	4.00	***	0.0040	3.65	***	0.0051	4.47	***
dayid	−0.0262	−6.25	***	−0.0276	−6.50	***	−0.0277	−6.55	***
afternoon	0.0569	0.90		0.0598	0.94		0.0588	0.93	
evening	−0.1222	−1.82	*	−0.1174	−1.74	*	−0.1225	−1.82	*
tues2thur	−0.2815	−3.49	***	−0.2803	−3.44	***	−0.2848	−3.51	***
friday	−0.0537	−0.48		−0.0673	−0.60		−0.0682	−0.61	
saturday	−0.2366	−2.37	**	−0.2406	−2.38	**	−0.2492	−2.48	**
sunday	0.1869	1.80	*	0.1670	1.59		0.1662	1.58	
constant	2.0261	4.42	***	2.1629	4.65	***	2.0241	4.33	***
		$\chi^2(20)$			$\chi^2(20)$			$\chi^2(22)$	
		18132.63	***		18251.05	***		18579.24	***

Table 7
Test for Declining Price Anomaly

This table presents the ordinary least square regression results on the price of a Gmail invitation using the successful auctions that were posted by the same seller and closed in the same hour. I run a regression for each of the top eleven sellers who managed to sell the most auctions within any given hour. The last row reports the results for the pooling regression. The common set of explanatory variables (see Table 3) is used here, in addition to the sequence number according to the closing time (*sequence*). Note that some of the explanatory variables were dropped out of the regression due to the lack of variation during the chosen hour. The estimated coefficient on the sequence number is reported along with its t-stat and the F-stat for the joint significance of all explanatory variables based on the robust standard errors. Also reported is the R^2. Statistical significance at the 1%, 5% and 10% level is denoted by ***, ** and *, respectively.

Auctions Sold	Seller Name	*sequence*	t-stat		F-stat		R^2
89	*zuckas*	0.0092	2.52	**	69.57	***	0.4650
76	*newyorkdiamonds*	0.0009	1.47		35.12	***	0.8944
58	*gimmeadollar*	0.0400	3.32	***	11.05	***	0.1841
47	*ericx*1001	−0.0342	−2.77	***	600.66	***	0.7226
47	*tshirtfreak.com*	−0.0029	−0.26		1.18		0.0510
40	*christmaseveryday*	0.0010	0.19		0.04		0.0008
38	*gimmeadollar*	−0.0166	−2.86	***	5.15	***	0.2200
38	*tshirtfreak.com*	0.0330	1.35		0.00		0.0991
36	*americanid* − −−	−0.0077	−1.19		1.41		0.0278
35	*tshirtfreak.com*	−0.0784	−1.97	*	1.95		0.0768
35	*zhang*8723	0.0276	0.93		0.52		0.0493
35 or higher		−0.0005	−0.11		41.87	***	0.5917

Figure 1
Daily Indices for eBay Auction of Gmail Invitations