Preliminary

Losing to Win: Reputation Management of Online Sellers

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Abstract

Reputation is generally considered an asset, especially in e-commerce markets. Any reputation system, however, elicits strategic responses from the sellers. Using panel data on a large random sample of online sellers from China's largest e-commerce platform, Taobao.com, we study how reputation affects revenue, prices, transaction volume, and survival likelihood as well as how sellers manage their reputation. We find that seller reputation has a substantial positive impact on established sellers, but new sellers fail to reap such benefits. Pursuing the long-run returns to reputation, new sellers actively manage their reputation by engaging in costly activities such as sales and switching product categories. In this "losing to win" process, new sellers may have spent too much resource to survive to next stage. Our results provide empirical support for the theory of career concern and reputation dynamics.

Keywords: Reputation, Information, e-commerce, Career Concern, Reputation Dynamics, Taobao.com

JEL Classification: L14, L15, L81, D82

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1 Introduction

Reputation is generally considered an asset, especially for entrepreneurs in e-commerce settings. In electronic markets such as eBay and Amazon marketplace, a consumer does not have the opportunity to carefully examine a product and has to make a purchase decision based on the description provided by the seller. A seller's reputation generated through the platform's feedback system therefore often determines whether a transaction takes place and the efficiency of trade. Without any trust-building mechanism such as reputation, uncertainty about product quality can hinder the operation of markets to the possible extreme of market failure (Akerlof, 1970).

In this paper, we study the return to reputation as well as how sellers manage their reputation. There is a large literature addressing the first question, but few studies have addressed the second.[1] It is only natural to ask if there is return of reputation, what sellers do to improve it. In fact, we argue that these two questions are intrinsically related. Only if there are significant returns to reputation will sellers spend resources to pursue higher reputation. To manage reputation, a seller may realize lower or even negative profits initially. Such reputation management behavior suggests that researchers need to consider seller heterogeneity in studying the effects of seller reputation. Foremostly, reputation may affect seller outcomes such as revenue, prices and sales for new and established sellers differently.

Identifying the differential effects of reputation on different types of sellers is, furthermore, confounded by the existence of unobserved seller heterogeneity. For example, the quality of an online seller's website design, which is typically unobservable, may affect the demand for this seller's products and henceforth her performance. Determined by the seller's past performance, her reputation is also influenced by the quality of her website design. As pointed out by Resnick, Zeckhauser, Swanson and Lockwood (2006) and Cabral and Hortacsu (2010), this creates a significant endogeneity problem. Most previous studies on this topic estimate cross-sectional regressions of prices or quantities sold on various measures of seller reputation.[2] These studies find that reputation seems to affect both prices and sales, but precise effects are often ambiguous (Dellarocas, 2003, 2006; Barari and Hortacsu, 2004). In some cases, there are no significant effects at all. Due to data limitations, how much seller reputation is worth, even for a given type of seller, can be a very challenging empirical question.

We bridge the gap in the literature by linking seller reputation management to reputation premium using a rich seller-month panel data from a large-scale online retail market. We are able to incorporate seller and month fixed effects and employ the instrumental variable method to deal with the endogeneity issue. More importantly, we are able to capture how sellers at different stages of life cycles manage their reputation and explain why there is sometimes lack of (and even negative) reputation effects. Ultimately, we can even track down a seller over time to check how reputation and the strategic responses it elicits attribute to her survival as a business.

[1] Mayzlin (2006), Dellarocas (2006), and Mayzline, Dover, Chaverlier (2012) study the manipulation of reviews.

[2] A notable exception is Luca (2011), which uses a panel of reviews from Yelp.com. Cabral and Hortacsu (2003) start from a cross section of sellers on eBay and construct a panel data of seller histories.

We obtained a 14-month (March 2010 - April 2011) panel on a large random sample of sellers from China's largest e-commerce platform --- Taobao.com (henceforth Taobao).[3] Like the Amazon Marketplace, Taobao is an online retail platform which offers meeting opportunities to buyers and sellers. It was launched in 2003 by the Alibaba Group, Inc. and became the undisputed market leader in e-commerce in China within two years. By the end of 2012, it had close to 500 million registered users and more than 800 million product listings per day. It sells on average 480,000 products per minute. According to the Alexa web traffic reporting, Taobao is ranked 11 globally. Among all 10 websites with more visits than Taobao, Amazon.com is the only online e-commerce website.[4]

At Taobao, seller reputation is easily quantifiable and highly visible to all parties of transactions. A seller's reputation is computed based on feedback from buyers. The feedback system used in Taobao is very similar to that of eBay with one important difference. In both platforms, a buyer can rate a seller (and vice versa) by leaving a positive (+1), neutral (0), or negative (-1) score after a transaction.[5] The rating score is simply the cumulative sum of these feedback scores for each transaction. The rating score is then categorized into a certain grade. The grades, together with the rating scores, are displayed in the most prominent place of a seller's website. The main difference between the feedback system of eBay and Taobao is that Taobao reports a user's seller reputation and buyer reputation separately, whereas on eBay a user has one rating score that depends on the feedback she gets as a seller as well as a buyer.

We have more than 1 million unique sellers in our random sample, whom we follow over time. For every month, we observe a seller's basic attributes, revenue, transaction volume as a seller, categories of business, and measures of seller reputation as well as her buyer reputation. We also observe a seller's cumulative transaction volume as a seller and as a buyer respectively since she registered at Taobao. We estimate the impact of a seller's reputation on her revenue, survival likelihood, and various other outcomes by regressing outcome variables on lagged reputation measures. We incorporate seller and month fixed effects in these regressions (except the regression of survival) to capture seller-invariant and time-invariant unobserved heterogeneity. Furthermore, we use a seller's cumulative transaction volume as a buyer, which is unobservable to buyers, to construct instruments for seller reputation to alleviate endogeneity bias associated with seller-month-specific unobserved heterogeneity. A seller's cumulative transaction volume as a buyer is unobservable to her potential buyers and thus does not affect the outcomes directly. It is however correlated with the seller's reputation as a seller because users spending more time on the platform simply buy more and sell more.

As argued above, it is important to separate new sellers from established sellers in these regressions. We use the information on when a seller first appears in our data and on her cumulative transaction volume as a seller to define whether she is a new or an established seller. We find that seller reputation has a substantial positive impact on established sellers. These established sellers are able to

[3] Taobao means "hunting for treasures" in Chinese.

[4] Retrieved on January 15, 2013. All other more popular websites are either a search engine (e.g. Google) or a social networking site (e.g. Facebook).

[5] The default feedback after a transaction is positive unless it is overwritten.

charge higher prices, sell higher volumes, and receive higher revenue as they climb the reputation ladder. As a consequence, at any point of time, better-reputed established sellers are more likely to survive for another six months. This pattern does not hold for new sellers. In fact, as reputation improves new sellers do not seem to benefit at all in terms of revenue and survival likelihood. A dissection of new sellers' behavior reveals their incentives to reach a critical level of reputation, often at a short-term loss. It seems that new sellers engage in various activities such as cutting prices, switching product categories, and selling in more categories in order to increase transaction volume, which can lead to high levels of reputation due to the close tie between reputation and transaction volume according to the feedback system. They push especially more aggressively when a next higher grade of reputation is within close reach. In this "losing to win" process, however, only a lucky few race to the top. Most new sellers may have spent too much resource to survive to next stage.

This paper contributes to the empirical literature on reputation. Examples in this literature include Resnick and Zeckhauser (2002), Dellarocas (2003), Chevalier and Mayzlin (2006), Houser and Wooders (2006), Resnick, Zeckhauser, Swanson and Lockwood (2006), Cabral and Hortacsu (2010) as well as Luca (2011). Different from prior work in the literature, we tie reputation management behavior to the long-run return to reputation. New sellers' growing reputation motivates more aggressive reputation management, which may deplete any gain from reputation in the initial phase. If we use a pooled data, we will have a mixture of new and established sellers, who respond to their reputation very differently. It is due to the existence of heterogeneous sellers and their different strategies responding to their existing reputation that we observe the often ambiguous effects of seller reputation as found in previous work.

Our findings are consistent with a "career concern" model as in Holmstrom (1999). In such a model, the employer observes the average value of past task outputs, and the employee works hardest early on in her career to build a reputation for competence.[6] Like Chevalier and Ellison (1999), who separate young and old managers in the study of career concern of mutual fund managers, we emphasize the importance of separating new sellers from established sellers in studying the effect of reputation.

Our empirical research is also embedded in the theoretical literature on reputation dynamics as in Klein and Leffler (1981) and Shapiro (1983). In a repeated game, players may realize lower or even negative profits initially, while the community learns their types. This initial phase is a possibility instead of a certainty because the profit margins need to be sufficiently high for "high-quality" sellers so that the promise of future gains from a reputation offsets the short-term temptation to cheat. Our results support a model of reputation dynamics in which there is a sufficiently high future return.

This paper proceeds as follows. Section 2 describes the setting and the data we use. Section 3 develops the empirical framework tailored to the setting and the data. Section 4 presents results and discusses their implications. Section 5 offers concluding remarks. We have an appendix to the paper which contains various robustness checks of our results.

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[6] However, Tadelis (2002) points out that when a seller's reputation is a tradable asset, the career concerns of young sellers from future returns have the same quantitatively effect that name-selling concerns have on old sellers. Therefore the reputation incentives can be "ageless" with an active market for reputations.

2 Settings, Data, and Descriptive Statistics

2.1 Taobao and its Online Feedback System

Launched by the Alibaba Group, Inc. on May 10, 2003, Taobao has become China's largest e-commerce platform. It grew rapidly with its market share having reached 59% by the end of 2005 and 80% by then end of 2008 (The Economist, 2006). Providing an excellent website service and technical support at practically no cost to online retailers,[7] Taobao soon dominated all other e-retailors, including eBay China and Amazon.cn. It has approximately 180 million registered users as of January 2010 (two months before our data were collected), among whom about 2 million consumer-to-consumer (C2C) sellers and 10 thousands business-to-consumer (B2C) sellers. It facilitated a gross merchandise volume of approximately RMB 200 billion in 2009 (about 29 billion US dollars) and RMB 400 billion in 2010 (about 60 billion US dollars). Taobao is still fast growing. By the end of 2012, it had close to 500 million registered users and more than 800 million product listings per day.

Besides requiring users to register an account with a valid personal ID, Taobao established and maintains a hugely successful online feedback system to build trust among participants in transactions.[8] Taobao's online feedback system mostly takes after eBay's, although transactions on Taobao are seldom through auctions.[9] Like eBay, Taobao's online feedback is bidirectional, meaning a buyer can rate a seller and vice versa after each transaction. The default rating score is positive (+1) unless it is overwritten with a neutral (+0) or negative (-1) score. On both eBay and Taobao, the rating score is simply the cumulative sum of these feedback scores from each transaction. The rating score is then categorized into grades. On eBay, the grades are represented by different colors of a star and whether a star is a shooting star. On Taobao, there are twenty grades going from one to five hearts, then one to five diamonds, then one to five crowns, and lastly one to five golden crowns. See Table 1 for the mapping from the rating score to the rating grade on Taobao. The relationship between rating scores and rating grades is nonlinear. As shown from Table 1, it becomes increasingly difficult to progress to higher grades. These twenty grades are well recognized by Taobao users. For example, a "two-golden-crown" seller is immediately considered a highly-reputed one. A user's rating grade, as expressed in these symbols, is displayed most prominently, accompanying every mention of the user ID in Taobao's website. For every seller, Taobao also reports the number of positive/neutral/negative ratings that a seller has received in the last week,

[7] Taobao adopted a policy of no registration fee for 3 years for registered buyers and C2C sellers since launching and has kept renewing this policy ever since. Two highlights of Taobao's services are Aliwangwang, an online instant messaging system to facilitate buyer-seller communication before a transaction, and Alipay, a financial intermediate service which allow buyers to receive products before payment and ensure sellers that they will be paid after delivering products. Advertising is Taobao's main income source.

[8] Linking users' online IDs with their personal IDs is an effective way to prevent users from registering multiple accounts and from restarting new accounts.

[9] Sellers occasionally use auctions for out-of-season sales.

last month, last six months, and before last six months as well as the percentage of positive ratings.[10] All these are shown in the seller's reputation profile, which takes a couple of clicks for interested parties to access.

Different from eBay, Taobao distinguishes a registered user's rating score as a seller from her rating score as a buyer. A seller's rating score as a buyer is also listed in the seller's reputation profile. A seller's rating score as a buyer is within close proximity of her transaction volume as a buyer, because very few sellers would leave a buyer a negative or neutral feedback after a transaction. In our data we observe the number of transactions that a user has engaged as a seller and as a buyer separately. This distinction is important because we use a seller's transaction volume as a buyer to create instruments for seller reputation. We explain the instrumental variable method more in detail in Section 3.3.

2.2 Data

Our data consist of a 25% random sample of all sellers on Taobao between March 2010 and April 2011. We focus on C2C sellers and drop all B2C sellers from the sample because almost all B2C sellers have brick-and-mortar stores and may have developed off-line reputation. In this random sample, a seller is defined as a user who has sold at least one item by April 2011. We only keep sellers who regularly sell at Taobao, that is, we drop sellers who are inactive in one third of the time span between their first and last appearances in the data, which amounts to about 18.5% of the sample.[11] We also drop sellers with obvious data reporting errors, which amounts to 1% of the sample.[12] In the end, we are left with more than 1 million unique sellers.

For each month that a seller is in the data, we observe her revenue, number of transactions, the accumulate number of selling and buying transactions since the registration, main business categories (as defined in Appendix 1), and number of business categories.[13] Dividing revenue by the number of transactions, we construct a rough measure of price. Moreover, we have several measures of seller reputation: a seller's rating score, rating grade (from 0 to 20), rating category (hearts, diamonds, crowns, and golden crowns), and percentage of positive ratings. Additionally, we observe a seller' basic attributes such as her date of Taobao registration, age, gender, her province of birth, as well as her province and city of current residency.

Table 2 describes the distribution of seller ratings. The majority of the seller-months in the data have rather low seller ratings, ranging from 1 heart to 5 hearts. About 40% of seller-months have achieved the diamond status (i.e., grades 6 to 10 or 251 to 10,000 points); but fewer than 2.5% have reached the crown category (i.e., above grade 11 or above 10001 points). There are so few golden-crown sellers (sellers

[10] Taobao also reports three dimensions of quality measures in a scale from 1 to 5, in a seller's reputation profile: 1) whether product matches description; 2) service quality; 3) delivery speed. These three dimensions are rated by buyers who choose to leave detailed reviews in the last 6 months. Our data do not contain these measures.

[11] Results are robust if we drop sellers who are inactive for one half of the time span or if we do not drop any occasional sellers.

[12] An example of such data reporting errors is that the number of *cumulative* seller transactions is not non-decreasing over time.

[13] We convert RMB to U.S. dollars using the exchange rate in July 2011. (1 U.S. dollar equals 6.472 RMB).

with grade 15 and above) that we lump crowns and golden crowns into one rating category, "crowns."[14] In later references, we often term these categories as rating categories I, II, and III, corresponding to hearts, diamonds, and crowns. Though not reported in the tables, an average Taobao seller is of age 30 and has acted as a seller for 5 out of 14 observed months. The average number of months elapsed since registration is much longer, suggesting an average user may have started her Taobao experience as a buyer long before starting her business as a seller. Among all unique sellers, 54% are women and 37% immigrated from birth providence to residence province. At any point of time, a seller's survival rate for another 6 months is 70% and for another 12 months is 54%.

Figure 1 shows the evolution of the number of Taobao sellers and their average rating scores and monthly revenue in the 14 months of our data span. Over time the number of sellers is increasing as Taobao is still a growing platform. The average seller rating score and average monthly revenue are also slightly increasing overtime. Even though new sellers join Taobao every month, potentially bringing down the average rating score and average monthly revenue, the existing and surviving sellers seem on average grow larger in size and their rating scores continue to grow. In February 2011, both the number of Taobao sellers and their average monthly revenue took a plunge: the Chinese New Year fell into this month and the entire nation (especially the post office, which delivers for most Taobao transactions) was on a break. While a large number of sellers just take a break during the holidays, some consider the time a natural point for exiting the market. As a result, there was a sharp drop in both the average monthly revenue and the number of Taobao sellers. There are no holiday effects on the average seller rating scores, which we attribute to the cumulative nature of rating scores.

3 Empirical Framework

3.1 Defining New and Established Sellers

As discussed earlier, the key to link reputation management to the reputation premium is to understand how sellers at different stages of life cycles strategically respond to her existing levels of reputation. We therefore need to distinguish new sellers from established sellers. A natural criterion is when a seller starts selling. A new seller can be a seller who has started selling recently, and an established seller has been selling for an extended period of time. However, determining when a seller starts selling is not straightforward in our 14-month sample.[15] More than 25% of sellers (corresponding to about a half of seller-months) appear in month 1 (March 2010), before which we do not observe their operating history. Thus we do not know when they start business. Even for a seller who first appears in an early month other than month 1 (say month 2) of our sample, we are still not sure whether she started business in month 2 because she might just have taken a short break from her business in month 1. We therefore

[14] In our 25% random sample, the highest grade reached is 3 golden crowns and only 30 seller-months fall into this category.

[15] We observe when a user registered on Taobao, but a user's registration time is not necessarily when she starts business. She may have registered so that she can purchase on Taobao.

combine the information on when a seller first appears in our sample with the information on her cumulative transaction volume to define whether a seller is a new seller or an established seller.

Specifically, we consider a seller an established one if the seller is in our data in month 1 and already has more than 250 transactions by that month. A seller of diamond status has at least 251 rating scores. Our data suggest that it takes quite some time for a seller to accumulate 251 transactions, which are necessary (but not sufficient) for her to reach the diamond status.[16] Therefore, we argue that a seller who appears in month 1 and has made at least 251 transactions by then can be reasonably regarded as having operated for a significant length of time.[17] This definition of established sellers rules out sellers who have been selling for a long time, but only made a few transactions from time to time. We think these sellers are most likely selling used household items occasionally at Taobao.

Instead of defining the remaining sellers as new sellers, we err on the side of caution and define a new seller as a seller: 1) who first appears during or after month 7; 2) who has been selling for no more than 6 months in the data, and 3) who has not reached 251 total transactions.[18] An explanation on each criterion is in order. First, the cleanest way to ensure a seller to have no prior history is to choose sellers who first appear at a rather late time, and we make it month 7.[19] Second, if a seller has operated for no more than 6 months, we do not consider her an established seller. Third, with this criterion, we potentially exclude Taobao sellers who have entered recently and rocketed to the diamond status (251 rating score) in a matter of days or a couple of months. We think these sellers cannot be safely regarded as new sellers because after having made to a critical level of rating scores these sellers may start to enjoy the return to reputation.

In our definitions of new sellers and established sellers, we try to be as conservative as possible in the baseline specification and conduct various robustness analyses using different definitions. In these robustness analyses, a new seller is always a seller who has started selling recently, and who has yet to reach a certain level of sale volume; an established seller is a seller who has been around for a long time so as to have reached a certain level of sale volume by the end of month 1. As we will show in the appendix, our results are robust to various starting month cutoffs, duration month cutoffs, and transaction volume cutoffs.

As shown in Table 3, there are stark differences between new sellers and established sellers. New sellers have much lower monthly revenue and sale volumes, charge lower prices, and sell in fewer categories than established sellers do. They also have much lower rating scores. Interestingly, the

[16] Our data show that among the new sellers (defined later) who survive for more than 6 months, only about 30% have reached 251 transactions by the end of the sixth month. Similarly, for new sellers who survive for more than 12 months, only about 50% have reached 251 transactions by the end of the twelfth month.

[17] We could define a seller as an established seller if the seller is observed to operate in, say, 12 out of 14 months in our data. But given that our panel is only 14 months long, then we only observe this seller as an established seller for at most 2 months, which renders the idea of using seller-fixed effect to deal with potential endogeneity concerns of reputation invalid.

[18] Note once a new seller crosses criteria 2) and 3) in a certain month (for example, the seller has reached 251 total transactions), we discard all observations of this seller from this month on. We do this in order to avoid contaminating our new seller definition.

[19] Our results are robust to different starting months from month 2 to month 8. We did not check robustness for month 9 and on because we want to follow a new seller for at least 6 months in our 14-month panel.

percentage of positive ratings is about the same for new sellers and established sellers, although the latter group has much smaller variances.

3.2 Empirical Framework

We use the above data to address two research questions. How much does a seller's rating affect its revenue and survival likelihood? And how does a seller manage its reputation? There are many challenges to answer these questions, most of them centering on the identification of the impact of reputation on outcomes. First, there is unobserved seller-level heterogeneity such as website design, responsiveness to customer inquiries, aftersales service, inventory management, delivery speed, etc. These seller attributes are observable to consumers and influence their decisions, but unobservable to researchers. As a result, they generate an endogeneity problem. Second, our data is an unbalanced panel as we only observe surviving sellers in our data. When the aforementioned seller heterogeneity also affects sellers' survival, we will have a "survival bias" in the OLS estimates of seller reputation. Lastly, there may be measurement error in the data and consequently "attenuation bias" in OLS estimates. While outcome variables such as revenue and transaction volume are aggregated for the entire month, only the snapshot of reputation on the 15th of each month is reported in our data.

The above problems will result in biased OLS estimates of reputation measures although the direction of bias is difficult to tell. For example, omitted variable bias will lead to upward bias in OLS estimates because omitted variables such as service quality are likely to correlate with seller reputation positively. However, survival bias may lead to downward bias in OLS estimates. Both well-reputed firms with low unobservable quality and poorly reputed firms with high unobservable quality may survive, implying that there may be a negative correlation between reputation and the omitted variable (Olley and Pakes, 1996). Furthermore, measurement error also leads to attenuation bias in the OLS estimates. To deal with these endogeneity issues, we include seller fixed effects in our regressions. We also use lagged reputation variables to alleviate the reverse causality concern because current sales do not affect last months' reputation. Specifically, we design our regressional framework as follows:

$$\begin{aligned} Outcome_{it} = {} & \alpha_0 + \alpha_1 RatingGrade_{i,t-1} + \alpha_2 Dummy\_RatingCategory_{i,t-1} \\ & + \alpha_3 RatingScore_{i,t-1} + \alpha_4 \%PositiveRating_{i,t-1} \\ & + \alpha_5 X_{it} + \mu_i + \omega_t + \varepsilon_{it} \end{aligned} \tag{1}$$

In this equation, we index a seller by i and a month by t. The outcome variables include the logarithms of current monthly revenues, prices, and current monthly transaction volume.[20] As independent variables, we include four measures of seller reputation available in the data. $RatingGrade$ is an integer from 0 to 18,[21] $Dummy\_RatingCategory$ includes 2 dummy variables: Category II (diamond)

[20] We also use whether the seller switched her main business category from last month and her total business categories as dependent variables when we look into a seller's strategies to manage reputation. We refrain from calling them outcome variables.

[21] The rating grade can range from 0 to 20 if we use the universe of the sellers. In the 25% sample we use, the highest rating grade achieved is 18.

and Category III (crown), and we set category I (heart) as the default category. *RatingScore* is the continuous rating score, and *%PositiveRating* is the percentage of positive ratings. We include all four measures to capture the potential nonlinearity in reputation effects. For example, when a seller's rating grade jumps from 5 to 6, she goes from five hearts to one diamond. There may be a huge increase in her revenue. The dummy variable "category II" is included to capture this possible spike. We use X_{it} to denote other time-varying seller attributes besides reputation. There is only one: the number of months elapsed since a seller registered at Taobao. All other seller attributes such as seller age and gender are time-invariant and therefore are absorbed by the seller fixed effect μ_i. We also include month dummies ω_t to capture seasonality and macro shocks etc. Lastly, the error term ε_{it} captures the seller- and time-variant unobserved heterogeneity. We assume ε_{it} to be *i.i.d.* across sellers, but ε_{it} can be persistent over time. For example, the display of merchandise on a seller's Taobao website and the speed of answering inquiries by the shopkeeper correlate over time and often determine transaction outcomes. For another example, a seller's inventory management, persistent over time (as inventory depends on what is left in stock from last month's transactions), affects whether delivery can be made on time and often determines whether a transaction can be made.

Equation (1) is designed to deal with the endogeneity problems of the reputation measures as best as we can. First, we use lagged reputation variables to ensure that reputation is measured prior to the realization of the outcome variables. Second, we include seller-fixed effects μ_i to capture the time-invariant part of unobserved heterogeneity. We believe a seller' unobserved heterogeneity is mostly fixed over time, for example, the website design and the accurateness of product description seldom change. However, to the extent that a seller's time-specific error term ε_{it} is serially correlated, there can still exist an endogeneity problem: ε_{it} may be correlated with seller reputation of last month. For example, a seller may have hired a great shop keeper last month, which increased her rating last month and this new shop keeper's excellent service carries on to this month, resulting in a positive correlation between her lagged reputation measures and current error term. To deal with this potential endogeneity problem, we adopt an instrumental variable strategy, detailed in the next subsection.

3.3 Instrumental Variables

At Taobao, a registered user can be a seller and a buyer at the same time, and Taobao records a user's transaction volume and ratings as a seller and as a buyer separately. The distinction between a user's seller role and her buyer role provides us a unique opportunity of finding instruments for seller reputation.

First, a seller's transaction volume as a buyer is not observed by any buyer directly. Even though a buyer can infer a seller's buyer transaction volume from her ratings as a buyer, which is listed on a side panel in a seller's reputation profile but at least a few clicks away from the seller's main page, we argue that a buyer has no reason to use this information to decide whether to purchase from this seller. First, various measures of seller reputation should provide sufficient information about the seller. Conditional on seller reputation, which is on prominent display, buyers should not rely on the seller's activities as a buyer for information. Second, it is highly unlikely that sellers buy inputs from Taobao, a retailing platform, to make products to sell. Most sellers are just occasional buyers for their own consumption, reflected by the low average transaction volume as a buyer. On average, a user has engaged in 1,376 transactions as a seller in our time span, but she has only engaged 131 transactions as a buyer. The fact that a Taobao seller's activity as a buyer is of much lower scale than her seller activity, supporting our argument that a seller's buyer activity is for own consumption instead of for purchasing inputs. Given the above two arguments, we believe that a seller's cumulative transaction volume as a buyer can be safely excluded from equation (1).

Do high-volume buyers typically have higher seller ratings? Regressions of seller ratings against a seller's transaction volume as a buyer, controlling seller fixed effects, time dummies, and time-variant seller attributes, clearly give an affirmation answer (See Appendix 2). We think the driving force behind this correlation is the quantity component of seller reputation measures: a user's seller rating score is based on the number of her accumulated transactions as a seller. A user who frequently purchases on Taobao in a month most likely spends a lot of time on the platform in that month and therefore completes a large number of transactions as a seller, which ultimately leads to a higher seller rating.

Lastly, we need a seller's transaction volume as a buyer last month to be uncorrelated with ε_{it}, which captures seller- and time-variant unobserved heterogeneity such as the display of merchandise on seller website and the speed of answering inquiries this month. When this seller/time-specific error term is serially correlated, it may be correlated with seller reputation of last month. However, we assume that it is uncorrelated with the seller's transaction volume as a buyer as of last month. One might argue that since a seller's transaction volume as a buyer is correlated with the time she spends on Taobao and thus correlated with the speed of her answering potential buyers' inquiries, it is correlated to the error term in the same period. However, note that we in fact use the month-t deviation of a seller's transaction volume as a buyer as instruments because we include seller fixed effects in the first stage of the IV regressions. The underlying identification assumption we impose is therefore that the month-t deviation from the average time that seller-i spends on Taobao is serially uncorrelated. In other words, we argue that although the quality dimension of a seller's time-variant unobserved heterogeneity could be persistent, the month-t deviation from the average time she spends on Taobao may be driven by idiosyncratic factors such as spotty Internet connections, commute costs, and air quality[22] and is therefore not persistent.

Given the above arguments, we use a seller's transaction volume as a buyer of last month to instrument for seller reputation variables, which is also lagged, in equation (1). Note that all seller rating variables (rating grade, rating category dummies, and rating score) are all constructed from one metric, a seller's rating score. In total, we have up to four endogenous variables. Analogously, we construct

[22] Sellers are more likely to engage in indoor activity (such as buying and selling in Taobao) when air quality is poor. Commute costs may have similar effects. Viard and Fu (2012) find that higher commute costs caused by Beijing motor vehicle driving restrictions increase television viewership significantly.

instruments from one metric, a seller's cumulative transaction volume as a buyer. Specifically, we create 1 grade variable (an integer from 0 to 13) and 14 grade dummies based on the cutoff points in Table 1.[23] In total, we use 16 instrumental variables in our baseline specification: the seller's transaction volume as a buyer, the constructed grade variable, and the 14 grade dummies. Results are robust if we use 2 constructed category dummies (diamonds and crowns) based on the cutoff points in Table 1 to replace the 14 grade dummies as instruments. As for the fourth measure of seller reputation, the percentage of positive feedbacks, we could use the percentage of positive feedbacks given to the user after a buying transaction. But there is little variation in this percentage as few sellers give a buyer neutral or negative feedbacks. Since there is no good instrument for the percentage of positive feedbacks, we do not interpret the coefficient causally.

3.4 Survival Regression

After measuring the impact of seller reputation on monthly outcome variables such as revenue, we consider its impact on survival likelihood. Ultimately, survival is a better indicator for underlying profitability than revenue, prices, and sales. If a seller benefits from higher reputation, she will be more likely to continue her business. For this purpose, we take snapshots of the data and investigate whether a seller with better reputation at that time has a higher survival likelihood six months later.[24] As above, we separate new sellers from established ones and estimate the effects of reputation on these two groups separately. Because our new sellers are sellers who start selling in month 7, we take the month-7 snapshot of new and established sellers and look at their month-13 survival outcomes respectively. According to our definition of new sellers, the new sellers in month 7 have been selling for under a month. To add more variation in new sellers' profiles, we repeat this exercise for the month-8 snapshot, which corresponds to the month-14 survival outcomes. We use a linear probability model:

$$\begin{aligned} Survival_i = \beta_0 + \beta_1 RatingGrade_i + \beta_2 Dummy\_RatingCategory_i \\ + \beta_3 RatingScore_i + \beta_4 \% PositiveRating_i \\ + \beta_5 X_i + \beta_6 \eta_{location\_trade} + \upsilon_i \end{aligned} \tag{2}$$

In equation (2), $Survival_i$ is a dummy variable equal to 1 if a seller i is still in the data six months later, and equal to 0 otherwise. We use the same set of seller reputation variables as in equation (1) but use their current values in the snapshot month. Note that in equation (2) we do not have the time dimension as we only observe the outcome variable once. For the same reason, we do not incorporate either seller- or month- fixed effects in this cross sectional regression; instead we include seller's location-trade- (location is a seller's residing province-city combination, and trade is her main business category) fixed effects $\eta_{location\_trade}$. We are also able to include all time-invariant seller attributes such as age, gender,

[23] The highest of a seller's transaction volume as buyer is 51,617, falling into grade 13 (50,001 to 100,000 points). Note the vast majority (over 90%) of the sellers have engaged in less than 1,000 transactions.

[24] Our data does not allow us to look at a longer time horizon such as 12 months. There is a possibility that our exit indicator also captures temporary inactivity of some users.But note that we have screened out most recreational sellers from our sample. Moreover, temporary inactivity could also be considered as a business failure.

months since registration in the snapshot month, etc., denoted by X_i. The error term υ_i is *i.i.d.* cross sellers.

Although we separate young sellers from established ones, in either regression sellers are heterogeneous along some important unobserved dimensions. For example, we do not have the exact business age of a seller (we do control the number of months since registration, which can be deemed as a proxy for business age). If we believe older firms are better-reputed, the error term υ_i is then correlated with all reputation measures. For example, surviving sellers tend to have higher unobserved quality which contributes to their reputation as well as survival. The issue here is that sellers who survive until the snap-shot month are a selected (along unobserved dimension) group. The correlated between υ_i and the reputation measures leads to biased OLS estimates as well, for which we use the same set of instrumental variables as we have used for equation (1).

We acknowledge that the instrumental variables we use here are less clean-cut for equation (2) than for equation (1). In equation (2) as we only use the data as a cross section, we are not able to use fixed effects. To the extent that a frequent buyer does not necessarily have better unobserved quality, our instrumental variables are still valid. This is a much stronger assumption that the one we used before: month-t deviation of how much time that a user spends on Taobao from the average time spent is not serially correlated.

4 Results

4.1 Do Established Sellers Receive Returns to Reputation?

A seller's reputation management strategy is motivated by the return to reputation in the long run. The magnitude of this return will determine the level of a new seller's effort in pursuing higher reputation. Therefore, the first question we need to answer is whether established sellers receive return to reputation. Estimation results reported in Table 5 deliver a strong affirmative answer to this question. The dependent variable is the logarithm of monthly total revenue in U.S. dollars plus a Chinese cent divided by 6.472, while 6.472 is the exchange rate on July 2011 (we add one Chinese cent to avoid taking logarithm of zero). We present eight specifications, gradually adding more reputation variables and alternating between OLS and IV results. The odd-numbered columns report OLS estimates, and the even-numbered columns IV estimates. We include seller fixed effects and month dummies in all specifications and report robust standard errors.

As we add more reputation measures into the regression, we can see coefficients remain relatively stable. The big change happens when we switch from OLS to IV regression. Some OLS estimates suffer upward bias (lagged rating grade coefficients), while others suffer downward bias (lagged rating category dummies and lagged rating scores). This suggests that different sources of endogeneity bias as discussed in Section 3.2 are counteracting each other, leading to ambiguous direction of OLS bias. Column (8), which shows IV estimates with all four reputation measures, reports substantial returns to reputation. All four reputation measures have significantly positive effects on revenue. Although one point increase in lagged rating scores leads to very little gain, one grade increase leads to a 37% increase in monthly total revenue.[25] Moreover, there are huge jumps in returns to reputation as a seller goes from heart to diamond or from diamond to crown. It's a whole new world once a seller makes the diamond status (and then makes the crown status) when the rating score is only increased by one point from 250 to 251 (for crown status it is from 10,000 to 10,001). As hearts, diamonds, and crowns are the most prominently displayed reputation symbols, this is suggesting that the salience of reputation symbols plays a big role in how buyers perceive them when making purchase decisions.

As revenue is simply price multiplied by quantity, we investigate the effects of seller reputation on prices and transaction volume separately. Table 6 reports these decomposed effects of seller reputation. The first two columns of Table 6 use the logarithm of price as the dependent variable, while the last two columns use the logarithm of transaction volume (plus 1).[26] We can see that higher reputation contributes to higher prices and higher transaction volumes for established sellers. The most robust finding is on the effects of lagged rating grade: according to the results in column (4), one grade increase leads to a large increase (21.7%) in the number of transactions even though one grade increase is associated with a slight increase in price (6.8%, column 2). In short, sellers with higher rating grades sell substantially more at a moderate price premium.

4.2 New Sellers: "Racing to Diamonds"

What about new sellers? Do better-reputed new sellers see immediate return to reputation? We repeat the regressions in Tables 5 and 6 for new sellers in Tables 7 and 8. Note that we do not have $Dummy\_RatingCategory$ in any of the specifications now because according to our definition of new sellers none of them has made it to the diamond status.

Different to results on established sellers, reputation does not seem to generate any returns. Let's first focus on the results across rating grades. As by definition new sellers have not made more than 251 cumulative transactions, we are looking at rating grade changes from one heart to 5 hearts. Across Tables 7 and 8, we can see that higher lagged rating grade is associated with (significantly) lower prices (Table 8, column 2) and (significantly) higher transaction volume (Table 8, column 4); and consequently, there is no revenue gain at a higher reputation grade (Table 7). Our interpretation of the results is that new sellers cut prices in order to jump to a higher grade because they foresee the long-run benefit of reputation. Before they reach a certain level of reputation, they engage in active reputation management such as sales and promotions to the extent that there is no immediate return to reputation. In Taobao, this is a well-known common practice by sellers named "Racing to Diamonds".

[25] The effect of one grade jump on percent increase of revenue is $exp(0.315)$ minus 1, which is about 0.37. Other quantitative effects reported in the rest of the paper are similarly calculated.

[26] The price and quantity proxies we use in these regressions are pretty rough because 1) we only observe the number of transactions, but not the composition of products in each transaction; 2) products sold across transactions and across sellers can be very different. Results regarding prices and transaction volumes need to be interpreted with these caveats in mind.

Sales and promotions are not the only means for a seller to attract more demand, create more sales, and build reputation. Another popular practice is to start out selling cheap and standardized products (for example prepaid cellphone refill cards) to accumulate seller ratings and then switch or expand to a business category with higher profit margin (say cellphones). Tables 9 and 10 provide support for such practices. In Table 9, we regress a dummy indicating whether the seller switched main business category from last month on reputation measures and other controls for new sellers and established sellers separately. Table 10 reports the results from a similar regression of the logarithm of the number of business categories the seller covers in the current month. The estimation results indicate that new sellers with a higher rating grade tend to switch the main business category (Table 9, column 2); and it is the opposite for established sellers (Table 9, column 4). Both new sellers and established sellers tend to diversify their products when they have higher rating grades, but new sellers expand their business categories much more (Table 10, columns 2 and 4).

Within a grade, however, we observe quite different reputational effects and (the lack of) reputation management. As rating scores increase within a grade, there are significantly lower transaction volumes (Table 8, column 4) and significantly lower revenues (Table 7). We do not see any price-cutting behavior (Table 8, column 2); in fact, prices are significantly higher as rating scores increase. We do not observe practices of switching main business category or increase the number of categories neither; in fact, as rating scores increase new sellers are significantly less likely to switch (Table 9, column 2) and sell in significantly lower number of categories (Table 10, column 2). Within a grade, a typical seller appears to neither enjoy the return to reputation nor do much to change it. There seems to be lack of incentives to get the sellers going within a grade. These results suggest that the main action of reputation management happens across rating grades, which are the most salient reputation measure.

4.3 When Next Rating Grade is within Close Reach

In all previous results we can see that the main effects of reputation occur across grades, instead of within a grade. This begs the question when exactly the main action of reputation management happens. The above results suggest that it happens when the seller is within close reach to the next higher grade. We define "marginal sellers" as sellers whose ratings are 10% within the lower bound of rating scores for the next higher grade.[27] We add a dummy variable indicating whether the seller is marginal or not into equation (1). As we control for rating score in these regressions, this marginal seller dummy should in principle have no effects on the outcome variables if there is no reputation management at play. Table 11 compares the marginal sellers' practices between new sellers and established sellers. In this table, for presentation purpose, we only report the estimated coefficient of the marginal-seller dummy. Each cell reports results for a different regression. For example, row 1 and column 1 reports the OLS estimate of the impact of marginal seller dummy on log revenue. Columns 2 and 4 report IV results for new sellers and established sellers respectively. For new sellers (column 2), the marginal sellers engage in a rather aggressive reputation management: they cut prices (row 2) to increase transaction volumes (row 3) so much that a higher grade brings lower revenue (row 1). Compared with the average sellers within a grade,

[27]Below one diamond, the steps for grade are so small that we define a marginal seller as one whose rating is 10% within the reach of at least one diamond (251 points on). Results are robust if we do not impose this modification.

the marginal sellers are much more likely to switch to a different main business category (row 4) and sell in many more categories (row 5). For established sellers (column 4), we see no effort of price cutting by marginal sellers (row 2). They do tend to sell more (row 3) and their revenues are higher (row 1). They are less likely to change their main business category (row 4) and sell slightly more in categories (row 5). Overall, it seems that marginal new sellers pursue higher reputation very aggressively, while there is no action from marginal established sellers.

4.4 Survival as a Consequence

By now we see starkly different effects of seller reputation on short-term seller outcomes and seller behavior across new sellers and established sellers. The next natural question is whether this difference results in any difference in the long run. To answer this question, we investigate the role of seller reputation on a seller's survival likelihood within 6 months.

In Table 12 we look at all sellers in month 7 in the data (September 2010) and study their survival outcome 6 months later (March 2011). We define a survival dummy (0 for exit and 1 for survival). Among these sellers, 49,578 are new sellers, and 97,165 are established sellers. In all specifications, seller attributes and seller location-trade fixed effects are included, and robust standard errors are reported in the parentheses. We present both OLS and IV results for comparison. From columns 2 and 4, we can see that an established seller's rating grade contributes to its survival likelihood significantly and positively, while this pattern does not hold for new sellers. There seems to be no effects of seller rating grade on a new seller's survival likelihood six month later. An increase in seller rating score even has significantly negative effects on a new seller's survival likelihood. Results are similar in Table 13, which replicates Table 12 with data on all sellers in month 8 (October 2010). Quantitatively, one grade increase in seller rating grade increases an established seller's survival likelihood within six months by 15% to 16%, but has no effects on a new seller.

The findings on the impact of reputation on the survival likelihood of new sellers and established sellers are consistent with the findings on what they do to manage (or enjoy) reputation. The contrast in results across these two groups suggests that new sellers may have spent too much resource in the process of accumulating reputation to survive to next stage. Upon starting their Taobao retail shop, new sellers engage in sales and promotions, switching main business categories, selling in more categories, …, all for the purpose of boosting transaction volumes, and in turn, reaching for higher seller ratings. They manage their reputation actively at the cost of short-run benefit. This "lose to win" strategy pushes a few sellers to the top of the reputation ladder; however, it proves to be too much to bear for an average new seller.

There is an established fact in economics literature: new, smaller firms are more likely to fail, which is often termed as "infant mortality." There are two major alternative explanations: first, new firms, which tend to small, are more likely to subject to idiosyncratic risk or industry downturn as they are constrained by limited internal capital accumulation or credit market; second, the entrepreneurs/managers of these firms engage in more risky behavior such as expanding too rapidly and undertake less sophisticated actions such as entering over-crowded local markets. The two alternative explanations offer an intriguing question: Is this "infant mortality" phenomenon nature or "nurture"? Our results on Taobao sellers' survival likelihood suggest that "nurture" plays a significant role. It seems to be what the new sellers do to accumulate reputation, instead of their intrinsic "quality" or "efficiency" levels, that determines their business longevity. The new shop owners may have comparable products, services, and perhaps better prices than established sellers do, but they have little reputation to catch buyers' attention and to earn their trust. As reputation can only be accumulated through transactions, these new sellers have to do whatever it takes to boost sales and earn reputation, often at steep cost, and only the fittest few will survive to enjoy the return to their hard-earned reputation. In this direction, our findings echo Foster, Haltiwanger, and Syverson (2012), which show that new plants are just as technically efficient as older plants, but new plants start with a considerably lower demand and only slowly catch up over time. In their paper, there is a "demand accumulation" process, such as building a customer base; in this paper, we have a "reputation accumulation" process which every new seller has to go through to catch up with established sellers, that is, if they survive at all. In fact, our "reputation accumulation" process is just a special case of the "demand accumulation" process, and our paper, just like theirs, helps to explain the rich, diverse, and often puzzling patterns in firm turnover and industry structure.

5 Conclusion

As Cabral and Hortacsu (2010) note, the "…eBay reputation system gives way to noticeable strategic responses from both buyers and sellers." Indeed, any reputation system elicits strategic responses from both sides of the market. However, much of the previous literature on reputation in both online and offline market focuses on the behavior of buyers instead on that of sellers. Our work fills in the blank by studying the strategic responses from the seller side of a large-scale online retail market. To summarize, using a large panel of online sellers on China's leading e-commerce platform, Taobao.com, we find that established sellers receive substantial return to reputation, but new sellers sacrifice short-run benefits of reputation in pursuits for the long-run return. In this "losing to win" process, new sellers may have spent too much resource to survive to next stage.

Due to data limitations, previous research mostly uses cross-sectional variations of seller reputation and outcomes such as prices and sales. Results are often plagued by endogeneity bias. Our identification strategy benefits from two advantages of our data. First, we have panel data and thus are able to use richer variation in the data. Furthermore, the operating history contained in the data allows us to distinguish from new sellers from established ones so we can recover the lifecycle effects of reputation. Second, we are aided by the availability of unique instrument variables. At Taobao, a seller is a buyer at the same time. A seller's cumulative transaction volume as a buyer affects the outcome variables only through the channel of affecting seller reputation, making it an ideal instrument.

More importantly, our empirical results help to reconcile the ambiguous, often contradicting results on the effects of reputation. Theories of "career concern" and "reputation dynamics" posit the possibility that seller reputation has a differential effect in different stages of a seller's lifecycle. Guided by these theories, we incorporate seller heterogeneity by distinguishing new sellers from established sellers and find that reputation has distinctively different effects on these two types of sellers. If a researcher takes only a cross section of the data and tries to evaluate the average effect of reputation on outcomes, he will obtain a mixture of different effects and consequently derive misleading conclusions.

Lastly, this research provides a first step toward understanding online entrepreneurship as we study the strategies and behaviors by small, entrepreneurial online sellers, who face competition from much more experienced retailers online and offline. Most existing research in economics focuses on established, mature firms. The evidence on how entrepreneurship originates and develops is rare as data on new business establishments are very limited in scope and contents.[28] The detailed records we obtain from Taobao about how the entrepreneurs achieve business growth provide valuable information on this topic. Understanding how small start-ups run by inexperienced entrepreneurs behave at Taobao not only informs the decisions of future entrepreneurs who face similar environments, but also informs the design of online reputation systems as well as relevant policies in a new, thriving market environment. According to our results, platform design and policies to help new sellers surviving initial stages of reputation accumulation will foster market competitiveness and trade efficiency in the long run. Moreover, a seller may have incentives to slack off at later stages of life cycle, suggesting a design of online feedback system which puts more emphasis on current rather than overall lifetime performance.

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[28] Exceptions are studies that use data from the Census Bureau, for example, Haliwanger, Jarmin and Miranda (2012), but these data are not public available and there are many restrictions in using these data.

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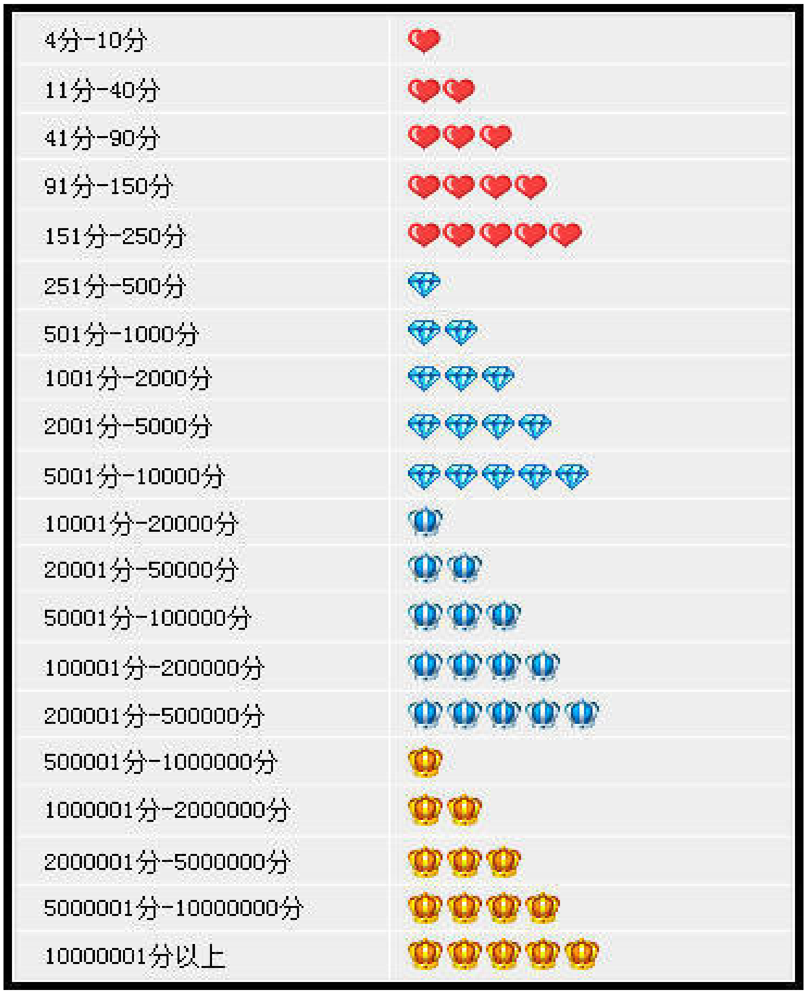
Tables and Figures

Table 1 Seller Rating Categories on Taobao



4分-10分
11分-40分
41分-90分
91分-150分
151分-250分
251分-500分
501分-1000分
1001分-2000分
2001分-5000分
5001分-10000分
10001分-20000分
20001分-50000分
50001分-100000分
100001分-200000分
200001分-500000分
500001分-1000000分
1000001分-2000000分
2000001分-5000000分
5000001分-10000000分
10000001分以上

Table 2 The Distribution of Seller Ratings

Seller Rating Score	Seller Rating Grade[29]	Seller Rating Category	Frequency	Percent	Cumulative
Below 4 points	0	I (hearts)	393,803	7.35	7.35
4 – 10 points	1		441,247	8.23	15.58
11 – 41	2		867,299	16.18	31.76
41 – 90	3		632,231	11.8	43.56
91 – 150	4		424,077	7.91	51.47
151 – 250	5		419,987	7.84	59.31
251 – 500	6	II (diamonds)	639,662	11.93	71.24
501 – 1,000	7		535,426	9.99	81.23
1,001 – 2,000	8		404,274	7.54	88.77
2,001 – 5,000	9		338,159	6.31	95.08
5,001 – 10,000	10		135,936	2.54	97.62
10,001 – 20,000	11	III (crowns)	74,895	1.4	99.02
20,001 – 50,000	12		39,300	0.73	99.75
50,001 – 100,000	13		8,819	0.16	99.91
100,001 – 200,000	14		2,954	0.06	99.97
200,001 – 500,000	15		1,292	0.02	99.99
500,001 – 1,000,000	16		236	4.40e-5	100
1,000,001 – 2,000,000	17		101	1.89e-5	100
2,000,001 – 5,000,000	18		30	5.60e-6	100
Total # seller /months			5,359,728	100.00	

[29] In our 25% random sample, the highest grade reached is 18 (3 golden crowns).

Figure 1 The Evolution of Taobao Sellers

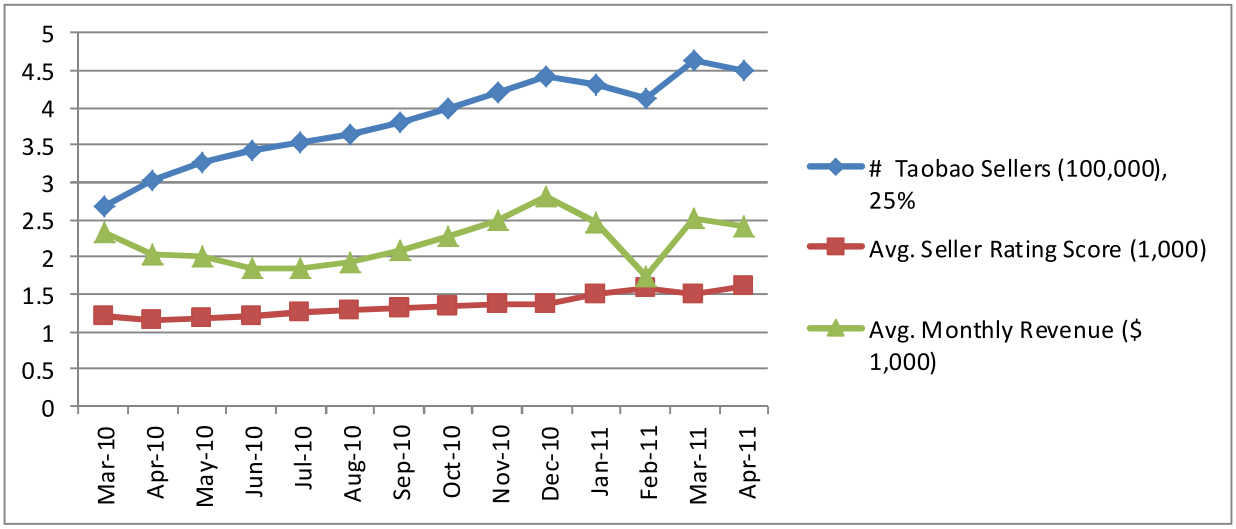


Table 3 Summary Statistics: New sellers vs. Established sellers

	New Sellers		Established sellers	
	Mean	Std. Dev.	Mean	Std. Dev.
Monthly total Revenue in $	449.930	6,268.734	5,871.053	43,750.100
Monthly total # Transactions	23.690	544.708	322.980	2,330.616
Price in $	59.389	668.564	62.554	381.261
Monthly total # Categories	1.740	1.619	3.250	3.552
If Switch Main Category	0.130	0.336	0.126	0.332
Seller Rating Score	36.645	51.451	4,762.959	23,995.410
Seller Rating Grade	1.810	1.436	8.213	1.615
Seller Rating Cat I	1	0	0.001	0.026
Seller Rating Cat II	n.a.	n.a.	0.907	0.290
Seller Rating Cat III	n.a.	n.a.	0.092	0.289
% Seller Pos. Ratings	0.995	0.044	0.995	0.008
# Months since Registration	20.710	2.109	39.233	9.816
# seller/months	1,031,403		1,311,452	
# sellers	473,152		107,276	

Table 4 Summary Statistics: a Seller's Cumulative Transaction Volume as a Buyer

	New Sellers		Established Sellers	
	Mean	Std. Dev.	Mean	Std. Dev.
Transaction Vol. as a Buyer	78.452	262.181	205.375	343.203
Transaction Vol. as a Buyer, grades from 0 to 13	2.219	1.888	3.950	1.934
Transaction Vol. as a Buyer in between:				
Below 4	0.240	0.427	0.044	0.204
4 − 10	0.139	0.346	0.044	0.204
11 − 41	0.244	0.430	0.159	0.365
41 − 90	0.154	0.361	0.198	0.398
91 − 150	0.086	0.280	0.157	0.364
151 − 250	0.066	0.248	0.150	0.357
251 − 500	0.050	0.218	0.156	0.363
501 − 1,000	0.016	0.127	0.071	0.258
1,001 − 2,000	0.004	0.061	0.019	0.136
2,001 − 5,000	0.001	0.034	0.004	0.060
5,001 − 10,000	2.7e-4	0.017	2.9e-4	0.017
10,001 − 20,000	7.37e-5	0.009	8.42e-5	0.009
20,001 − 50,000	1.45e-5	0.004	7.45e-6	0.003
50,001 − 100,000	0	0	9.70e-7	0.001
# seller/months	1,031,403		1,311,452	
# sellers	473,152		107,276	

Table 5 Established Sellers: Impact of Seller Reputation on log Revenue

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
L. Rating Grade	0.332***	0.466***	0.330***	0.261***	0.325***	0.284***	0.333***	0.315***
	(0.007)	(0.045)	(0.007)	(0.073)	(0.007)	(0.076)	(0.007)	(0.076)
L. Rating Category II			-0.023	17.060	-0.015	15.629	-0.043	15.642
			(0.170)	(11.432)	(0.170)	(11.411)	(0.170)	(11.350)
L. Rating Category III			0.011	20.057*	0.008	18.089	-0.007	17.867
			(0.171)	(11.938)	(0.171)	(12.000)	(0.171)	(11.926)
L. Rating Score in 10k					0.028***	0.175	0.030***	0.167
					(0.006)	(0.137)	(0.006)	(0.132)
L. % Pos. Ratings							24.420***	31.948***
							(2.409)	(3.323)
Months from Regis.	107.398***	107.448***	107.402***	107.686***	107.414***	107.722***	107.373***	107.636***
	(1.394)	(1.392)	(1.394)	(1.392)	(1.394)	(1.390)	(1.394)	(1.390)
R - Squared	0.131	0.130	0.131	0.087	0.131	0.095	0.131	0.098
# seller/months	1,234,176							
# sellers	104,138							

- Note 1: In this table and all following ones, standard errors are reported in parentheses. *significant at the 10 percent level. **significant at the 5 percent confidence level. ***significant at the 1 percent level.
- Note 2: from Table 5 to Table 11, we include seller- and month- fixed effects in all specifications. Standard errors in these tables are clustered at the seller level.

Table 6 Established Sellers: Impact of Seller Reputation on log Price and log Transaction Volume

	log Price		log Transaction Volume	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
L. Rating Grade	0.033***	0.066*	0.184***	0.197***
	(0.002)	(0.035)	(0.005)	(0.046)
L. Rating Category II	-0.005	2.912	-0.088	6.173
	(0.050)	(4.537)	(0.078)	(6.679)
L. Rating Category III	-0.009	1.869	-0.074	7.995
	(0.051)	(5.150)	(0.079)	(7.079)
L. Rating Score in 10k	-0.002**	0.153	0.020***	-0.066
	(0.001)	(0.125)	(0.004)	(0.091)
L. % Pos. Ratings	0.816*	-0.599	19.554***	24.327***
	(0.478)	(0.871)	(1.915)	(2.406)
Months from Regis.	0.010***	-0.019***	23.097***	23.260***
	(0.0003)	(0.003)	(0.317)	(0.317)
R - Squared	0.022	n.a[30]	0.079	0.017
# seller/months	1,189,225		1,234,176	
# sellers	104,138		104,138	

[30] In IV regression models, the model sum of squares can be negative because the residual sum of squares is more than the total sum of squares, resulting in a negative R-squared. We suppress the reporting of R-squared in such situations.

Table 7 New Sellers: Impact of Seller Reputation on log Revenue

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
L. Rating Grade	-0.584***	-0.837***	-0.242***	-0.017	-0.244***	-0.010
	(0.008)	(0.039)	(0.011)	(0.100)	(0.011)	(0.100)
L. Rating Score in 10k			-131.106***	-241.066***	-130.779***	-242.889***
			(2.753)	(27.528)	(2.753)	(27.500)
L. % Pos. Ratings					2.283***	2.205***
					(0.248)	(0.256)
Months from Regis.	-39.329***	-39.615***	-39.630***	-39.952***	-39.635***	-39.959***
	(0.876)	(0.875)	(0.875)	(0.876)	(0.875)	(0.876)
R - Squared	0.088	0.086	0.092	0.089	0.092	0.089
# seller/months	558,251					
# sellers	229,445					

Table 8 New Sellers: Impact of Seller Reputation on log Price and log Transaction Volume

	log Price		log Transaction Volume	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
L. Rating Grade	-0.005	-0.321***	0.012***	0.542***
	(0.004)	(0.034)	(0.004)	(0.042)
L. Rating Score in 10k	30.441***	124.405***	-125.608***	-311.020***
	(1.063)	(9.537)	(1.195)	(11.713)
L. % Pos. Ratings	0.155*	0.266***	0.774***	0.589***
	(0.083)	(0.085)	(0.089)	(0.101)
Months from Regis.	0.015***	0.048***	-4.626***	-4.998***
	(0.002)	(0.009)	(0.170)	(0.172)
R - Squared	0.011	n.a	0.161	0.075
# seller/months	519,131		558,251	
# sellers	229,269		229,445	

Table 9 New Sellers vs. Established Sellers:
Impact of Seller Reputation on Switching Main Business Category

	New Sellers		Established Sellers	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
L. Rating Grade	-0.027***	0.028**	-0.016***	-0.021***
	(0.002)	(0.013)	(0.001)	(0.009)
L. Rating Category II			-0.029*	-1.055
			(0.017)	(1.291)
L. Rating Category III			-0.019	-0.980
			(0.018)	(1.362)
L. Rating Score in 10k	-0.251	-17.343***	-0.0002	-0.003
	(0.418)	(3.743)	(0.0003)	(0.397)
L. % Pos. Ratings	-0.0003	0.020	0.186	0.397
	(0.031)	(0.032)	(0.198)	(0.285)
Months from Regis.	-1.155***	-1.182***	2.138***	2.149***
	(0.047)	(0.048)	(0.045)	(0.045)
R - Squared	0.005	n.a.	0.004	n.a.
# seller/months	558,251		1,234,176	
# sellers	229,445		104,138	

Table 10 New Sellers vs. Established Sellers: Impact of Seller Reputation on log Category Count

	New Sellers		Established Sellers	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
L. Rating Grade	0.013***	0.137***	0.028***	0.044***
	(0.001)	(0.011)	(0.001)	(0.012)
L. Rating Category II			-0.047***	1.197
			(0.018)	(1.660)
L. Rating Category III			-0.001	1.456
			(0.019)	(1.744)
L. Rating Score in 10k	-15.517***	-61.648***	0.07***	0.001
	(0.328)	(2.938)	(0.002)	(0.017)
L. % Pos. Ratings	0.060***	0.017	4.844***	5.639***
	(0.023)	(0.025)	(0.415)	(0.529)
Months from Regis.	0.693***	0.592***	1.378***	1.401***
	(0.029)	(0.030)	(0.042)	(0.043)
R - Squared	0.047	n.a.	0.015	n.a.
# seller/months	558,251		1,234,176	
# sellers	229,445		104,138	

Table 11 New Sellers vs. Established Sellers: What Do Marginal Sellers Do?

		New Sellers		Established Sellers	
		(1)	(2)	(3)	(4)
		OLS	IV	OLS	IV
(1)	Dep. Var.: log Revenue	-1.551***	-0.735***	0.217***	0.308***
		(0.112)	(0.228)	(0.008)	(0.043)
(2)	Dep. Var.: log Price[31]	0.305***	-0.344***	0.001	-0.017
		(0.047)	(0.082)	(0.002)	(0.027)
(3)	Dep. Var.: log Transaction Volume	-0.965***	0.365***	0.135***	0.211***
		(0.039)	(0.094)	(0.005)	(0.026)
(4)	Dep. Var.: Dummy Switch main category?	-0.023	0.099***	-0.011***	-0.012**
		(0.016)	(0.031)	(0.001)	(0.005)
(5)	Dep. Var.: log Category Count	-0.122***	0.217***	0.024***	0.040***
		(0.012)	(0.025)	(0.001)	(0.006)
# seller/months		558,251		1,234,176	
# sellers		229,445		104,138	

Note: In this table, each cell (coefficient + standard errors) is from a different regression and all coefficients reported are for the marginal seller dummy.

[31] In this regression, for new sellers the number of seller-months is 519,131, and the number of sellers is 229,260; for established sellers the number of seller-months is 1,189,225, and the number of sellers is 104,138.

Table 12 New Sellers vs. Established Sellers: Impact of Seller Reputation on Survival Likelihood

Month 7 Snap Shot

	New Sellers		Established Sellers	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Rating Grade	0.069***	0.046	0.043***	0.144***
	(0.004)	(0.049)	(0.001)	(0.019)
Rating Category II			-0.008	-2.129
			(0.104)	(6.730)
Rating Category III			-0.064	-2.811
			(0.104)	(6.797)
Rating Score in 10k	-7.674***	-21.480	-0.003***	0.020
	(1.240)	(15.473)	(0.0004)	(0.023)
% Pos. Ratings	0.145***	0.192***	1.741***	1.298***
	(0.031)	(0.038)	(0.204)	(0.297)
Months from Regis.	-0.002***	-0.001***	0.0003***	0.00003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Seller Age	0.003***	0.004***	-0.0002***	-0.0001
	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Seller Gender	0.002	0.001	0.0001*	-0.004
	(0.005)	(0.005)	(0.002)	(0.003)
If Province Immigrant	-0.008	-0.006	0.001	-0.006**
	(0.006)	(0.007)	(0.003)	(0.003)
R - Squared	0.028	0.001	0.038	n.a.
# sellers	49,578		97,165	

Note: In Table 12 and Table 13, we include seller location-trade- fixed effects in all specifications. Standard errors in these tables are clustered at the location-trade- level.

Table 13 New Sellers vs. Established Sellers: Impact of Seller Reputation on Survival Likelihood

Month 8 Snap Shot

	New Sellers		Established Sellers	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Rating Grade	0.077***	0.034	0.062***	0.151***
	(0.003)	(0.034)	(0.001)	(0.018)
Rating Category II			0.176	0.873
			(0.140)	(10.501)
Rating Category III			0.092	0.284
			(0.140)	(10.542)
Rating Score in 10k	-8.200***	-18.194*	-0.003***	-0.001
	(0.793)	(9.986)	(0.001)	(0.012)
% Pos. Ratings	0.086***	0.166***	1.653***	1.155***
	(0.029)	(0.034)	(0.216)	(0.256)
Months from Regis.	-0.002***	-0.001***	1.26e-6	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Seller Age	0.003***	0.004***	-0.0003**	-0.0002
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Seller Gender	-0.004	-0.004	0.004	-0.001
	(0.004)	(0.004)	(0.002)	(0.003)
If Province Immigrant	-0.006	-0.004	0.001	-0.004
	(0.004)	(0.005)	(0.003)	(0.003)
R - Squared	0.034	n.a.	0.055	n.a.
# sellers	84,820		95,745	

Online Appendix: Not for publication

Appendix 1: Taobao Main Business Categories

Appendix 2: First Stage Results in Regressions Using Instrumental Variables

Appendix 3: Robustness Checks for Table 5 to 13 (*to be finished*)

- A 3a: Results are robust if we use 12 months as duration cutoff in the definition of new sellers. In the specification, we define new sellers as sellers: 1) who first appears after month 2 (including month 2), 2) who has been selling for no more than 12 months in the data, and 3) who has not reached 251 total transactions. For survival regressions we take month 2 snapshots of sellers and look at their month-14 survival outcomes.
- A 3b: Results are robust if we do not use transaction volume cutoff in the definition of new sellers. We also use a more relaxed starting month cutoff. In the specification, we define new sellers as sellers: 1) who first appears after month 4 (including month 4), and 2) who has been selling for no more than 6 months in the data. For survival regressions we take month 4 snapshots of sellers and look at their month-10 survival outcomes.
- A 3c: Results are robust 1) if we drop sellers who are inactive in one half of the time span between their first and last appearances in the data; or 1) if we do not drop any "occasional" sellers at all.

Appendix 1: Taobao's Main Business Categories

Category ID	Main Business Category
0	unclassified
11	computer hardware/desktops/network
14	digital cameras/camcorders/cameras
16	women's apparel
20	video games/accessories
21	home/storage and organization/gifts
23	antique/collectibles
25	toys/dolls/mannequin
26	automobile accessories/motorcycles/bicycles
27	lamps/lights/bath
28	men's accessories
29	pet/pet food
30	men's apparel
33	books/magazines/newspaper
34	music/movies/movie stars
35	baby formula/baby nutrition
40	Tengxun text messaging service
99	Internet games
1101	laptops
1201	MP3/MP4/iPod
1512	cell phones
1625	intimates/underwear/lounge wear
1801	skin care/body care/essential oil
2128	decor/curtains/rugs
2813	adults/anti-contraceptives/family planning
50002766	snacks/nuts/tea/local specialty
50002768	personal care/health/massage
50004958	calling card recharging
50005700	watches/fashion watches
50005998	early education
50006842	luggage/handbags/bags
50006843	women's shoes
50007216	flowers/cakes/gardening
50007218	office supplies

50008075	live shows/coupons
50008090	digital accessories
50008163	bed/pillows/towels
50008164	furniture/custom made furniture
50008165	children's clothes and shoes
50008907	IP card/Internet phones/calling card number
50010388	athletic shoes
50010404	accessories/belts/hats/scarves
50010728	sports/yoga/fitness
50010788	cosmetics/fragrance/hair care/tools
50011150	miscellaneous
50011397	jewelry/diamonds/jade/gold
50011665	Internet games accessories
50011699	men's active wear
50011740	men's shoes
50011949	vacation/discount airfares/discount hotels
50011972	TV & entertainment electronics
50012081	cell phones made in China
50012082	kitchen appliances
50012100	small appliances
50012164	flash drives/removable disks
50012472	nutrition/food
50013698	test
50013864	fashion jewelry/women's accessories
50013886	outdoors/hiking/camping/travel
50014442	Shanghai Expo 2010 merchandise
50014811	Internet services/custom-made software
50014812	diapers/feeding
50016348	cleaning supplies
50016349	kitchen & dining
50016422	groceries/frozen food/meal delivery
50016891	Internet game vertical market???
50017300	musical instruments
50018004	office supplies
50018222	assembled computer
50018252	group discount (like groupon)
50018264	routers
50019379	Yitao (search engine service developed by Taobao)
50019780	creative design

50020275	nutrition/drugs
50020276	nutrition/food
50020332	interior decoration
50020485	home hardware
50020579	home fixtures (such as light switch)
50020611	office furniture
50020670	arts/crafts/sewing
50020808	wall decoration
50020857	home misc.
50022517	pregnancy/maternity
50022703	home appliances
50023282	wig
50023575	purchase through agent
50023717	virtual world

Note: Taobao's definition of main business category is evolving over time, often depending on the popularity of the category. In the data we have, Taobao defines 87 main business categories. We manually merged some categories which are similarly defined. For example, we merged category 0 (unclassified) with category 50011150 (miscellaneous). Results are robust to whether we perform the merge or not. We also deleted observations which are listed under category 50019379 (Yitao), because Yitao is a search engine e service which does not lead to any transaction at Taobao.

Appendix 2: First Stage Results in Regressions Using Instrumental Variables

Table A2.1 First Stage Results: Regressions with Seller Fixed Effects

	Table 5, Column 8				Table 7, Column 6	
Instrument: L. Buyer Transaction Volume	(1) L. Rating Grade	(2) L. Rating Cat. II	(3) L. Rating Cat. III	(4) L. Rating Score (10k)	(5) L. Rating Grade	(6) L. Rating Score (10k)
In 10k	4.455***	-1.030***	1.021***	4.946***	2.867***	0.014***
	(0.452)	(0.123)	(0.122)	(1.055)	(0.455)	(0.002)
Grade (0-13)	-2.369***	0.558**	-0.555**	-2.568**	-3.171***	-0.014***
	0.858	(0.242)	(0.240)	(1.234)	(0.612)	(0.003)
Grade 1	-21.743**	4.925*	-4.896*	-23.216*	-33.799***	-0.152***
	(9.612)	(2.696)	(2.672)	(13.886)	(6.515)	(0.033)
Grade 2	19.132**	4.373*	-4.347*	-20.670	-30.241***	-0.137***
	(8.760)	(2.455)	(2.433)	(12.664)	(5.905)	(0.030)
Grade 3	-16.516**	3.826*	-3.801*	-18.120	-26.767***	-0.121***
	(7.908)	(2.214)	(2.195)	(11.446)	(5.295)	(0.027)
Grade 4	-13.894**	3.269*	-3.247*	-15.572	-23.274***	-0.106***
	(7.058)	(1.979)	(1.957)	(10.231)	(4.685)	(0.024)
Grade 5	-11.329**	2.706	-2.688	-13.010	-19.805***	-0.090***
	(6.209)	(1.734)	(1.719)	(9.022)	(4.077)	(0.020)
Grade 6	-8.823*	2.140	-2.126	-10.438	-16.414***	-0.074***
	(5.364)	(1.495)	(1.482)	(7.820)	(3.471)	(0.017)
Grade 7	-6.358	1.570	-1.560	-7.846	-13.103***	-0.059***
	(4.523)	(1.257)	(1.246)	(6.630)	(2.867)	(0.014)
Grade 8	-3.978	0.996	-0.990	-5.215	-9.945***	-0.045***
	(3.689)	(1.020)	(1.011)	(5.459)	(2.268)	(0.011)
Grade 9	-1.697	0.439	-0.437	-2.558	-6.918***	-0.031***
	(2.868)	(0.787)	(0.780)	(4.322)	(1.682)	(0.008)
Grade 10	0.470	0.094	0.091	0.172	-4.011***	-0.018***
	(2.073)	(0.560)	(0.555)	(3.262)	(1.121)	(0.006)
Grade 11	1.807	0.355	0.350	3.861	-1.650***	-0.007**
	(1.365)	(0.355)	(0.351)	(2.692)	(0.608)	(0.003)
R - Squared	0.377	0.042	0.045	0.030	0.014	0.014
F statistic	390.70	30.32	29.07	14.88	652.48	398.77
# seller/months	1,234,176				558,251	
# sellers	104,138				229,245	

Note: all first stage regressions include seller fixed effects. Standard errors are clustered at the seller level. These results apply to all regressions under the same specification (Table 5 to 10), except that results are slightly different in log price regressions in which the number of observations is smaller (Table 6, col. 2 and Table 8, col. 2), and in regressions including "marginal" variable (Table 11).

Instrumented: L. Rating Grade, L. Rating Category II, L. Rating Category III, L. Rating Score in 10k

Included instruments: L. % Pos. Ratings, Months from Registration, 13 month dummies (month 2 to month 14)

Excluded instruments: L. Buyer Transaction Volume in 10k, L. Buyer Transaction Volume Grade (an integer from 0 to 13), L. Buyer Transaction Volume Grade Dummies (14 dummies)

Dropped due to collinearity: month 14 dummy, L. Buyer Transaction Volume Grade Dummies 12, 13, and 14

Table A2.1 First Stage Results: Survival Regressions (Month 7 Snapshot)

	Table 11, Column 2		Table 11, Column 4			
Instrument: L. Buyer Transaction Volume	(1) L. Rating Grade	(2) L. Rating Score (10k)	(3) L. Rating Grade	(4) L. Rating Cat. II	(5) L. Rating Cat. III	(6) L. Rating Score (10k)
In 10k	9.044***	0.034***	3.470***	-0.482***	0.482***	2.102
	(2.071)	(0.007)	(0.811)	(0.184)	(0.184)	(2.718)
Grade (0-13)	0.535	0.009***	-1.808	0.079	-0.078	-0.966
	(0.710)	(0.002)	(1.183)	(0.245)	(0.245)	(2.687)
Grade 1	6.437	0.085***	-18.075	0.746	-0.743	-10.719
	(6.139)	(0.021)	(11.826)	(2.442)	(2.442)	(26.862)
Grade 2	6.062	0.077***	-16.318	0.683	-0.679	-9.879
	(5.435)	(0.018)	(10.647)	(2.198)	(2.198)	(24.195)
Grade 3	5.748	0.069***	-14.397	0.600	-0.597	-8.886
	(4.732)	(0.016)	(9.467)	(1.954)	(1.954)	(21.529)
Grade 4	5.369	0.061***	-12.409	0.511	-0.508	-7.893
	(4.034)	(0.014)	(8.290)	(1.711)	(1.711)	(18.872)
Grade 5	4.957	0.053***	-10.449	0.417	-0.415	-6.894
	(3.343)	(0.011)	(7.114)	(1.467)	(1.467)	(16.223)
Grade 6	4.499*	0.044***	-8.543	0.322	-0.321	-5.888
	(2.658)	(0.009)	(5.940)	(1.225)	(1.225)	(13.588)
Grade 7	3.888*	0.035***	-6.538	0.210	-0.209	-4.799
	(1.994)	(0.007)	(4.770)	(0.984)	(0.984)	(10.981)
Grade 8	3.150**	0.026***	-4.536	0.085	-0.084	-3.613
	(1.370)	(0.004)	(3.612)	(0.745)	(0.745)	(8.424)
Grade 9	1.763**	0.014***	-2.733	-0.006	0.007	-2.329
	(0.821)	(0.003)	(2.472)	(0.511)	(0.511)	(5.967)
Grade 10			-0.919	-0.097	0.097	-0.815
			(1.377)	(0.289)	(0.289)	(3.658)
R - Squared	0.056	0.054	0.067	0.044	0.044	0.016
F statistic	18540.74	62146.87	173.72	87.80	88.52	29.15
# sellers	49,578		97,165			

Note: all first stage regressions include location-trade- fixed effects. Standard errors are clustered at the location-trade- level. Results are similar for Table 12, where we use month 8 snap shot.

Instrumented: L. Rating Grade, L. Rating Category II, L. Rating Category III, L. Rating Score in 10k.

Included instruments: L. % Pos. Ratings, Months from Registration, Seller Age, Seller Gender, Whether Seller immigrated from province of birth.

Excluded instruments: L. Buyer Transaction Volume in 10k, L. Buyer Transaction Volume Grade (an integer from 0 to 13), L. Buyer Transaction Volume Grade Dummies (14 dummies).

Dropped due to collinearity: (Column 2) L. Buyer Transaction Volume Grade Dummies 10, 11, 12, 13, and 14; (Column 4) L. Buyer Transaction Volume Grade Dummies 11, 12, 13, and 14.