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 for [illegible] of sellers [illegible]

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.

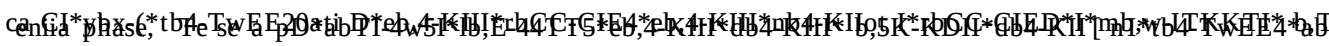
As argued above, it is important to separate new sellers from established sellers in these regressions. We use the information on when a seller first appears in our data and on her cumulative transaction volume as a seller to define whether she is a new or an established seller. We find that seller reputation 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. Thi syetter aes ot hold for he



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

FigurrhI-4w5K*olbCK-5TEI*dbxD*30 b,xE-5xxD*an

b4-KIIT4*tb,CC5-IE4TTD*,C*s*mbTI-x4x*eb,4-KIIIorb] T?aTKD-45KbI-Ixxs

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:

$$\begin{aligned} Outco\ e_{it} = {} & \alpha_0 + \alpha_1 \text{[redacted]} n\ Grade_{i,t-1} + \alpha_2 Du\ \ y\_\text{[redacted]} n\ Cate\ ory_{i,t-1} \\ & + \alpha_3 \text{[redacted]} n\ \ core_{i,t-1} + \alpha_4 \%Pos\text{[redacted]} ve\text{[redacted]} n_{i,t-1} \\ & + \alpha_5 X_{it} + \mu_i + \omega_t + \varepsilon_{it} \end{aligned} \tag{1}$$

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. [redacted]*n Grade* is an integer from 0 to 18,[21] *Du y_*[redacted]*n Cate ory* 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. [redacted] is the continuous rating score, and [redacted] 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

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. Table 4 reports summary statistics of these 16 instruments. Combining Tables 3 and 4, we can see that an average new seller has engaged in 450 transactions as a seller in our time span, but she has only engaged 78 transactions as a buyer. In the meantime, an average established

$$
\begin{aligned}
[illegible]va_i = \beta_0 &+ \beta_1 [illegible]n\ Grade_i + \beta_2 Du[illegible]y\_[illegible]n\ Cate[illegible]ory_i \\
&+ \beta_3 [illegible]n\ core_i + \beta_4 \%Positive[illegible]n_i \\
&+ \beta_5 X_i + \beta_6 \eta_{[illegible]on\_trade} + \upsilon_i
\end{aligned} \tag{2}
$$

In equation (2), $[illegible]va_i$ 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 $\eta_{[illegible]on\_trade}$. We are also able to include all time-invariant seller attributes such as age, gender, months since registration in the snapshot month, etc., denoted by X_i. The error term υ_i is *i.i.d.* cross sellers.

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 *Diamond_Category* in any of the specifications now because according to our definition of new sellers none of them has made it to the diamond status.

[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.

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,

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, 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) and rescale it by 100 for the presentation of results. 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

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

g G,E4-KIILwD* [illegible]

possibility that seller reputation has a differential effect in different stages of a seller's lifecycle. Guided by

*eb,4--KIII*dK-[illegible]TwEE4*4-xTC*ofb,I-IECxE*ttb4-TwEE4*hbb4-KIII*db4-KIII*ogbTI-4w5K*eb,4-KIII*nb4-KIII*ebCK-TED

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Table 2 The Distribution of Seller Ratings

Seller Rating Score	Seller Rating Grade[29]	Seller Rating Category	Frequency	Percent	Cumulative
Below 4 points	0		393,803	7.35	7.35

I (hearts)

Figure 1 The Evolution of Taobao Sellers

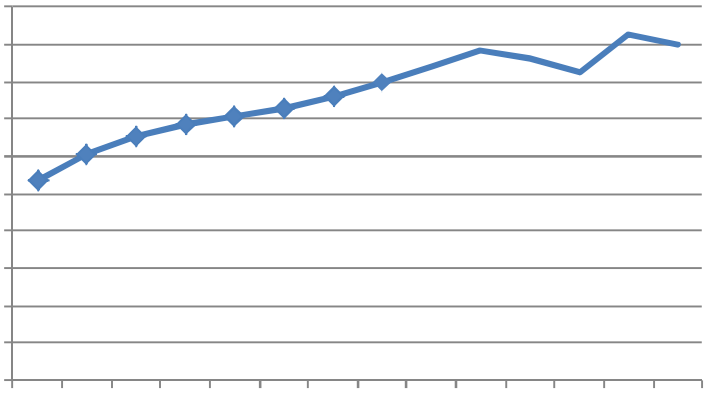

Table 3 Summary Statistics: New sellers vs. Established sellers

	New Sellers	Established sellers

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***	000)mCDDxhTTxKh l aCDI5hTTxKh l a h aW		

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	

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

	New Sellers	Established Sellers

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

	New Sellers	Established Sellers

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

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*rbCC-CIEK*fb,C45*/bw-E] T?aT2 [*50˙w-I12081bTI-4K-TEDT* b] Txa210*eb,4-KIII*arbIx-5x

50˙w-I12081airr

50011III*nb4-Kk5Tsshoel-x4x*cb,4-KIII*arITKKTC*ebCK-TEDT*lb,w4hT˙aT2 [*50012082bTI5K* b,T4II-DD*vbx-wTT

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:	(1)	(2)	
L. Buyer Transaction Volume	L. Rating Grade	L. Rating	
			(2)
			Grade

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

	Table 11, Column 2	Table 11, Column 4
Instrument:		
L. Buye*eb,4-KIII**+Za.WhCa.%hTa.Z$Bh4a/Gh	ÿ ÿ ÿaq/h'aqhChwhwhThCCxIhT4TThcmaZ/a.BS.cmaZ/a.BEDq	