MICHIGAN
ROSS SCHOOL OF BUSINESS

Working Paper

Quantifying Cross-Network Effects in Online C2C Platforms

Junhong Chu
NUS Business School

Puneet Manchanda
Stephen M. Ross School of Business
University of Michigan

Ross School of Business Working Paper
Working Paper No. 1248
September 2014

This work cannot be used without the author's permission.
This paper can be downloaded without charge from the
Social Sciences Research Network Electronic Paper Collection:
http://ssrn.com/abstract=2494948

UNIVERSITY OF MICHIGAN

Quantifying Cross-network Effects in Online C2C Platforms

Junhong Chu*

Puneet Manchanda

July 2013
This version: September 2014

* Junhong Chu is Associate Professor of Marketing at NUS Business School, National University of Singapore, Singapore, and Puneet Manchanda is Isadore and Leon Winkelman Professor and Professor of Marketing at the Ross School of Business, University of Michigan, USA. The authors are very grateful to Taobao.com for providing data for this research. They also thank Tat Chan, John Deighton, Savio Kwan, Thomas Otter, Xu Zhang, participants at Cambridge, Oxford, KU Leuven, Frankfurt Goethe, LMU Munich, the 2014 AMA-ECMI-EMAC Marketing Symposium, Rotterdam, the 2013 Yale China India Insights Conference, New York, NY, the 11th and 10th Marketing Dynamics Conferences and the 9th Invitational Choice Symposium at Erasmus University, the Netherlands, for valuable comments and suggestions. Finally, they gratefully acknowledge financial support from the Asian Consumer Insights Institute at Nanyang Business School, Singapore, the National University of Singapore HSS Seed Fund R-316-000-102-646 and Phelps Faculty Fund at the Ross School of Business, University of Michigan. The authors can be contacted via email at bizcj@nus.edu.sg (Chu) and pmanchan@umich.edu (Manchanda). The usual disclaimer applies.

Electronic copy available at: http://ssrn.com/abstract=2494948

Abstract

Consumer-to-consumer (C2C) platforms have become a major engine of growth in Internet commerce. This is especially true in countries such as China, which are experiencing a big rush towards electronic commerce. The emergence of such platforms gives researchers the unique opportunity to investigate the evolution of such platforms by focusing on the growth of both buyers and sellers. In this research, we build a structural model to quantify two-way cross-network effects (buyers on sellers and sellers on buyers) in Taobao.com, the world's largest online C2C platform based in China. Specifically, we investigate the relative contributions of different factors that affect the growth of buyers and sellers on the platform. Our results suggest that there is a significant, large and positive cross-network effect on both sides of the market. In other words, the installed base of either side of the platform has propelled the growth of the other side. Interestingly, this effect is asymmetric with the installed base of sellers having a much larger effect on the growth of buyers than vice versa. The growth in the number of buyers is driven primarily by the seller's installed base and product variety with increasing importance of product variety. The growth in the number of sellers is driven by buyer's installed base, buyer quality, and product price with increasing importance of buyer quality. We also investigate the nature of these cross-network effects over time. We find that the cross-network effect of sellers on buyers increases and then decreases to reach a stable level. In contrast, the cross-network effect of buyers on sellers is relatively stable. We discuss the policy implications of these findings for the platform.

Keywords: *Platforms, Two-sided markets, Cross-network effect, Emerging markets, China*

Electronic copy available at: http://ssrn.com/abstract=2494948

1. Introduction

Consumer-to-Consumer (C2C) platforms such as eBay, Amazon's Marketplace, Taobao.com, and OLX.in have become a major engine of growth in electronic commerce. This is especially true in countries such as China that are experiencing a big rush towards electronic commerce. The emergence of such platforms represents a new phenomenon as they have scaled up to very large numbers very quickly. For example, the Chinese C2C network, Taobao.com, had 435 million consumers participating as buyers and 7 million as sellers in less than a decade after its formation. The factors that have enabled this growth and size have been novel revenue generating mechanisms, e.g., charging sellers only for value-added services, and the platforms' agnostic attitude towards product assortment, allowing buyers and sellers to make choices on what to offer. While there is a rich body of work on platform economies and two-sided markets, starting with the pioneering work of Rochet and Tirole (2003), the focus has typically been on platform competition, pricing structure and business model determination (e.g., Caillaud and Jullien 2003, Armstrong 2006, Rochet and Tirole 2006) and less on the factors determining platform evolution and growth. In addition, most empirical work on platform markets has usually been set in "conventional" or offline markets, such as VCRs, game consoles, PDAs, media (TV, newspaper, and magazines), payment systems, and yellow pages (e.g., Ohashi 2003, Rysman 2004, Nair, Chintagunta and Dubé 2004, Clements and Ohashi 2005, Wilbur 2008, Dubé, Hitsch and Chintagunta 2010, Liu 2010, Sun, Rajiv and Chu 2014). Much of the extant research on online C2C platforms such as eBay has focused on the auction mechanism and recommendation system, rather than on the evolution and growth of the platform.

In this paper, we focus on the evolution and growth of online C2C platforms. Specifically, we investigate the evolution of the platform both from the buyer's and the seller's perspective as well the nature of buyer and seller interactions over the platform's lifecycle. We look at three novel questions. First, how large is the cross-network effect (CNE) on both sides of the platform? As for any network, the growth and evolution of one side has a direct impact – the cross-network effect (CNE) - on the growth and evolution of the other side. Our objective is to quantify the CNEs - the impact of the installed base of sellers on the growth of buyers and the impact of the installed base of buyers on the growth of sellers, while allowing for asymmetric effects. Second, we examine how the non-network factors (e.g., product variety, product price, and buyer quality) affect the growth of the two sides of the network. We contrast the effect of non-network factors with the network effects towards the growth of the network. Finally, we allow both the network and non-network effects to vary over time beginning from the platform's inception.

In order to do this, we exploit a new data set from www.taobao.com, the world's largest online C2C platform based in China. Taobao.com (referred to as Taobao for the rest of the paper) has 7.1 million sellers and 435 million buyers (as of December 2012). Each day there are 728 million unique items on the "shelf" for sale and 75 million unique viewers, generating 13 million transactions and 1.61 billion yuan (USD 258 million)[2] in revenues. Our data set contains daily observations on the number of platform participants, the assortment of products on offer, and the revenue from buyers and sellers. A major distinguishing feature of our data set is that our data start from the first day of Taobao's operations - May 11, 2003.

Using a structural approach to model buyer's and seller's platform joining decisions jointly, we identify a large, significant and positive CNE on both sides of the platform market. However, we find that the CNE is asymmetric: the installed base of sellers has a much larger effect on the growth of buyers than vice versa. Further, the growth in the number of buyers is driven primarily by the seller's installed base and product variety with increasing importance of product variety over time. In contrast, the growth in the number of sellers is driven by the buyer's installed base, buyer quality, and product price with increasing importance of buyer quality over time. The two CNEs demonstrate different temporal patterns. Specifically, the CNE of sellers on buyers increases and then decreases to reach steady state. In contrast, the CNE of buyers on sellers is relatively stable. We examine the policy implication of our findings.

The rest of the paper is organized as follows. In Section 2, we review the relevant literature. We set up the econometric model in Section 3, describe the institutional setting in Section 4, summarize the data and explain the variable operationalization in Section 5, and describe the estimation in Section 6. We report the main findings, results of the robustness checks, and managerial implications in Section 7 and conclude in Section 8.

---

[2] For the sake of exposition, we use 6.23 yuan to 1 USD as the exchange rate (the rate reported at xe.com on Dec 31, 2012) throughout the paper. This rate was around 8.50 yuan at the time of Taobao's inception, dropped to 6.8 yuan in 2008 and then was steady till about 2010 and then declined to 6.23 yuan at the end of 2012 (all data from xe.com).

2. Literature review

Research on two-sided markets has a relatively short history (see Rysman 2009 and Sriram et al. 2013 for an overview). Rochet and Tirole (2003, 2006), Caillaud and Jullien (2003) and Armstrong (2006) each provide a theoretical framework for two-sided markets to explain how the price structure is determined when either a monopoly platform sets prices, or two platforms compete. A common feature present in all this theory work is that the benefit of joining a platform for any agent depends on the number of agents from the other side on the same platform. This relationship can be summarized by the CNE, testifying to the importance of the existence and magnitude of the CNE. While our paper does not investigate the price structure because the platform under study adopts free pricing for both sides of the market. However, the theoretical work cited here guides in determining the drivers of platform growth as well as the possible functional forms for capturing buyer and seller utility.

The empirical work on network effects is somewhat limited, though growing at rapid pace.[3] One stream of work (e.g., Shankar and Bayus 2003, Ohashi 2003, Park 2004) has focused on direct network effects. In other words, the estimated network effect quantifies the benefit (or cost) that agents obtain from the presence of other agents on the same side, rather than those on the complementary side (usually due to lack of data). Gandal, Kende and Rob (2000) are among the first to explicitly model cross-network externalities. They measure the effect of hardware prices and software titles in the diffusion of CD players, and find that a 10% increase in CD titles would have as large an effect as a 5% price cut. Rysman (2004) estimates the importance of CNEs in the market for Yellow Pages and finds two-way positive cross-network externalities whereby advertisers value consumer usage and consumers value advertising. Ackerberg and Gowrisankaran (2006) estimate the size and importance of network externalities in the automatic clearing house (ACH) banking industry, and find that most of the impediment to ACH adoption is from the large customer fixed cost of adoption. Wilbur (2008) explicitly models the two-way cross-network interactions in the

[3] Given that our setting is a monopoly platform that does not charge sellers and buyers, we only focus on work related to network effects. For work that has focused on competition, price structure and market power, see Kaiser and Wright (2006), Chandra and Collard-Wexler (2009), Jin and Rysman (2012), Seamans and Zhu (2014), Argentesi and Filistrucchi (2007), Liu (2010) and Pattabhiramaiah, Sriram and Sridhar (2013). For work on market outcomes and consumer welfare, see Chen and Xie (2007), Dubé, Hitsch and Chintagunta (2010), Fan (2013) and Song (2013).

television industry and finds a negative effect of the number of advertisements on audience size (viewers are ad averse) and a positive effect of audience size on advertiser demand (advertisers are viewer loving).

A few studies have extended this literature by quantifying the evolution of cross-network externalities. Nair et al. (2004) quantify the size of CNEs in the personal digital assistants (PDA) market with competing incompatible technology standards, and find significant and growing effect of software provision on hardware adoption. Clements and Ohashi (2005) measure the effects of hardware price and software variety in the diffusion of video game systems in the U.S. market between 1994 and 2002. They find that introductory pricing is an effective practice at the beginning of the product cycle, and expanding software variety becomes more effective later.

Our paper is closely related to these two studies, but with some notable differences. First, our empirical context is a unique and different two-sided market, viz. a monopoly C2C online platform that has adopted free pricing for both sides of the market throughout the platform's lifecycle. Thus the drivers for the platform's growth are very different from other platforms. Second, we explicitly quantify two-way CNEs, i.e., buyers on sellers and sellers on buyers, and their evolution over the platform's lifecycle, while Nair et al. (2004) and Clements and Ohashi (2005) focus on one side, i.e., software titles on hardware adoptions. Third, in contrast to their separate estimation of the two sides and instrumental variables techniques, we model the decisions of the two sides *jointly*. Fourth, our finding on the relative importance of network factors versus non-network factors provides qualitative new insights. For example, both Nair et al. (2004) and Clements and Ohashi (2005) find an *increasing* importance of CNE in the diffusion of hardware over the platform's lifecycle. In contrast, we find a *decreasing* importance of network factors and increasing importance of non-network factors in the growth of the platform. Therefore, our research adds to and complements the literature on the network effects and their evolution.

3. Model

We take a structural approach to model the platform's evolution by focusing on the growth of buyers on one side of the market and that of sellers on the other side. We consider a monopoly platform that provides a marketplace for buyers and sellers to transact with each other. It charges buyers and sellers, respectively, A^B and A^S (fixed) membership fees and a^B and a^S commissions per transaction. Both membership fees and transaction charges can be zero or negative (subsidies). A seller charges price p_t for selling a product to a buyer at time t. We next derive a buyer's and a seller's probabilities of joining the platform and the platform's market shares on the buyer and seller sides.

3.1 Buyer side model

Previous research on two-sided markets has documented that the utility of a representative buyer joining the platform depends on (a) the utility from each transaction and (b) the number of potential transactions (Rochet and Tirole 2003, 2006, Armstrong 2006). Buyer i has a reservation value $\overline{v}_t$ and receives a net marginal surplus $b_t^B = \overline{v}_t - p_t - a_t^B$ for each transaction. The number of transactions depends on (i) the number of sellers on the platform or the installed base of sellers at time $t-\tau$, $N_{t-\tau}^S$, (ii) product variety V_t, which increases the chance of match between buyers and sellers, (iii) seasonality and holiday factors X_t, (iv) some unobserved (to the researcher) factor(s) ξ_t^B, and (v) a buyer idiosyncratic factor ε_{it}^B. The net utility of a representative buyer at time t is:

$$U_{it}^B = f(b_t^B) f(N_{t-\tau}^S, V_t, X_t, \xi_t^B, \varepsilon_{it}^B) - A^B \tag{1}$$

In our empirical context, $A^B = 0$ and $a_t^B = 0$. Since we do not observe $\overline{v}_t$, we assume it to be proportional to product price p_t. Assuming the buyer's net utility from each transaction and the potential number of transactions take a Cobb-Douglas utility function (cf. Rysman 2004), we have buyer i's indirect utility of joining the platform as:

$$U_{it}^B = \beta_0 + \beta_{1\bar{t}} \ln(N_{t-\tau}^S) + \beta_2 \ln(p_t) + \beta_3 V_t + \beta_4 X_t + \xi_t^B + \varepsilon_{it}^B \tag{2}$$

In this setup, $\beta_{1\bar{t}}$ measures the effect of seller's installed base on buyer's utility, i.e., the CNE of sellers on buyers. In order to capture the evolution of CNE over time, we allow this coefficient to be time (year and month) varying. β_2 represents the effect of product price on buyers, β_3 is the marginal effect of product variety on buyers, and β_4 stands for the effect of seasonality and holidays. Assuming ε_{it}^B follows i.i.d. extreme value distribution and the utility of not joining the platform is normalized to zero, we have the buyer's probabilities of joining and not joining the platform respectively as:

$$P_{it}^{B} = \frac{\exp(\beta_0 + \beta_{1\bar{t}}\ln(N_{t-\tau}^{S}) + \beta_2\ln(p_t) + \beta_3 V_t + \beta_4 X_t + \xi_t^B)}{1+\exp(\beta_0 + \beta_{1\bar{t}}\ln(N_{t-\tau}^{S}) + \beta_2\ln(p_t) + \beta_3 V_t + \beta_4 X_t + \xi_t^B)} \tag{3}$$

$$P_{it}^{B,0} = \frac{1}{1+\exp(\beta_0 + \beta_{1\bar{t}}\ln(N_{t-\tau}^{S}) + \beta_2\ln(p_t) + \beta_3 V_t + \beta_4 X_t + \xi_t^B)} \tag{4}$$

Under the assumption that buyers "single home" (a reasonable assumption in our empirical context as described below), a buyer's probability of joining the platform is the same as the platform's market share of buyers, z_t^B.[4] Thus, the platform's relative market share is:

$$\ln(\frac{z_t^B}{z_t^{B,0}}) = \ln(\frac{n_t^B / M_t^B}{(M_t^B - n_t^B)/M_t^B}) = \beta_0 + \beta_{1\bar{t}}\ln(N_{t-\tau}^{S}) + \beta_2\ln(p_t) + \beta_3 V_t + \beta_4 X_t + \xi_t^B \tag{5}$$

where n_t^B is the number of new buyers in time period t and M_t^B is the market potential for buyers at the beginning of time t.

3.2 Seller side model

We derive the seller's probability of joining the platform and the platform's market share of sellers in a similar manner. As before, a seller's utility of joining the platform depends on (a) profit margin from each transaction and (b) the number of potential transactions (Rochet and Tirole 2003, 2006, Armstrong 2006). The profit margin per transaction is the difference between the product price and marginal cost c_t, less the commission cost the seller has to pay to the platform, $b_t^S = p_t - c_t - a_t^S$. The number of potential transactions depends on (i) the number of buyers on the platform or the installed base of buyers at time $t-\kappa$ $N_{t-\kappa}^{B}$, (ii) buyer's quality Q_t^B, which increases the attractiveness of the platform, (iii) seasonality and holiday factors X_t, (iv) some unobserved factors ξ_t^S, and (v) seller idiosyncratic factor ε_{jt}^S. The net utility of a representative seller j joining the platform at time t is:

$$U_{jt}^{S} = f(b_t^S) f(N_{t-\kappa}^{B}, Q_t^B, X_t, \xi_t^S, \varepsilon_{jt}^S) - A^S \tag{6}$$

In our empirical context, $A^S = 0$ and $a_t^S = 0$. Since we do not observe c_t, we assume sellers adopt cost-plus pricing, which is a very reasonable assumption in our empirical context because the majority of sellers are individuals or part-time sellers and treat selling on the platform as a secondary occupation. Assuming the seller's profit margin per transaction and the potential number of transactions take a Cobb-Douglas utility function, we have seller j's indirect utility of joining the

[4] As we discuss later, we only have access to aggregate data. Hence we cannot accommodate heterogeneity in preferences for either buyers or sellers.

platform as:

$$U_{jt}^{S} = \alpha_0 + \alpha_{1\bar{t}} \ln(N_{t-\kappa}^{B}) + \alpha_2 \ln(p_t) + \alpha_3 Q_t^{B} + \alpha_4 X_t + \xi_t^{S} + \varepsilon_{jt}^{S} \tag{7}$$

In this utility setup, $\alpha_{1\bar{t}}$ measures the effect of the installed base of buyers on seller's utility, i.e., the CNE of buyers on sellers. In order to capture the evolution of CNE over time, we allow this coefficient to be time (year and month) varying. α_2 represents the effect of product price on seller's utility, α_3 denotes the effect of buyer quality, and α_4 stands for the effect of seasonality and holidays. Assuming ε_{jt}^{S} follows i.i.d. extreme value distribution and the utility of not joining the platform is normalized to zero, we have the seller's probabilities of joining and not joining the platform respectively as:

$$P_{jt}^{S} = \frac{\exp(\alpha_0 + \alpha_{1\bar{t}} \ln(N_{t-\kappa}^{B}) + \alpha_2 \ln(p_t) + \alpha_3 Q_t^{B} + \alpha_4 X_t + \xi_t^{S})}{1 + \exp(\alpha_0 + \alpha_{1\bar{t}} \ln(N_{t-\kappa}^{B}) + \alpha_2 \ln(p_t) + \alpha_3 Q_t^{B} + \alpha_4 X_t + \xi_t^{S})} \tag{8}$$

$$P_{jt}^{S,0} = \frac{1}{1 + \exp(\alpha_0 + \alpha_{1\bar{t}} \ln(N_{t-\kappa}^{B}) + \alpha_2 \ln(p_t) + \alpha_3 Q_t^{B} + \alpha_4 X_t + \xi_t^{S})} \tag{9}$$

Under the assumption that sellers "single home" (see below), the seller's probability of joining the platform is the same as the platform's market share of sellers, z_t^S. Thus, the platform's relative market share is:

$$\ln\left(\frac{z_t^{S}}{z_t^{S,0}}\right) = \ln\left(\frac{n_t^{S}/M_t^{S}}{(M_t^{S} - n_t^{S})/M_t^{S}}\right) = \alpha_0 + \alpha_{1\bar{t}} \ln(N_{t-\kappa}^{B}) + \alpha_2 \ln(p_t) + \alpha_3 Q_t^{B} + \alpha_4 X_t + \xi_t^{S} \tag{10}$$

Where n_t^S is the number of new sellers in time period t and M_t^S is the market potential for sellers at the beginning of time t. We now have the system of equations (5) and (10) that can be taken to the data for estimation. We collect the notation into Table 1 for ease of exposition.

At this point, it is worth pointing out that we do not model direct network effects as a contributory factor to the growth of the platform. We discuss this in detail in Appendix A.

4. Institutional Setting

As noted earlier, our data are provided by www.taobao.com, a China-based online platform.[5] Taobao is the world's largest online consumer-to-consumer (C2C) platform, both by registered users and by revenues. By December 31, 2012, Taobao had 7.1 million sellers and 435 million buyers. Its

[5] The data are provided to us under an NDA that allows us to publish analyses and results but not the raw data.

transactions in 2012 totaled 590 billion yuan or $95 billion. Given these numbers, Taobao essentially represents the C2C platform market. We now provide a brief introduction to the platform, its history, organizational structure and business model as many of our modeling choices are based on these details.

The parent company of Taobao is Alibaba (China) Group, a privately-owned company[6] that does business in many areas of electronic commerce, including business-to-business (B2B, www.alibaba.com for international trade, and www.1688.com for China's domestic trade) for small and midsize enterprises, C2C (www.taobao.com), business-to-consumer (B2C, www.tmall.com), online payment system (www.alipay.com), online advertising (www.etao.com), group buying (www.juhuasuan.com), portal service (cn.yahoo.com), and cloud computing (www.aliyun.com).[7]

Taobao began operations in May 2003. The first seller registered on May 11, 2003. In the early years, Taobao's growth was slow. Taobao adopted a "free" policy - free registration and free transactions for buyers, and free registration, free listing, and free transactions for sellers. It also created Aliwangwang, a Skype-like communication device that allows buyers and sellers to fully communicate and exchange information to facilitate transactions. It also created Alipay, a PayPal-like escrow payment system that resolved the payment and trust issue for Internet commerce in a country where credit card usage was far from universal and buyers and sellers had mutual distrust for each other in online transactions.[8] As a result, Taobao quickly gained market acceptance. As of the end of 2012, Taobao accounted for about 75% of China's online retailing, and has an over 95% market share in China's online C2C commerce. It can therefore be considered as having a virtual monopoly in C2C platforms.[9]

[6] The Alibaba group went public in Hong Kong 2007, back to private in 2012 and has recently announced its intentions to go public in the United States in the third quarter of 2014.

[7] For more information, please visit http://page.1688.com/shtml/about/ali_group1.shtml

[8] For example, in the Chinese market context, it was very novel that buyers pay *before* seeing the actual goods they buy and sellers deliver the goods *before* receiving payment.

[9] Taobao was launched in May 2003 as part of a defensive action by the Alibaba group against eBay that, in 2003, was firming up a deal to enter China in collaboration with a Chinese partner, eachnet.com. eBay Eachnet adopted a business model similar to its U.S. counterpart – transactions cleared via an auction process, sellers had to pay registration and listing fees while buyers did not pay registration and transacted for free. eBay Eachnet did not employ an escrow based system and also forbade buyers and sellers to communicate directly with each other. Due to the lack of localization, eBay Eachnet never enjoyed the success and popularity in China that it did in the US and Germany and was quickly overtaken by the local upstart, Taobao. In three short years, Taobao had over two-thirds of the Chinese C2C market and eBay exited China, dissolving the partnership in Dec 2006 (Wang 2012). Therefore, it is clear that Taobao was a virtual monopoly after 2006 but did face some competition in the 2003-2006 period. As we do not have any data on the number of participants on eBay Eachnet, the outside good described in Sections 3.1 and 3.2 between 2003-06 combines not joining any C2C platform (i.e., shopping at physical stores) and joining eBay Eachnet. In a later section (7.2.6), we drop the initial years from our analysis to see if that affects our results.

Taobao continues its free policy to date. Specifically, buying at Taobao is free. In order to register as a buyer, an agent has to provide a valid cell phone number or an email account. Once a person chooses a user name and a password, Taobao sends an activation code or link to the phone number or email account, typically on the same day (or occasionally, the next day). Once activated, a buyer remains registered as a buyer, even if s/he does transact. Selling at Taobao is also free – free registration, no membership fee, no annual fee, no listing fee, and no transaction commissions. Registering as a seller at Taobao is via a "real-name authentication" registration process.[10] The seller must be at least 18 years old, hold a valid photo ID, and pass a simple test (mainly on Taobao's rules and regulations). The process of verification and approval takes from two to seven days. This variation in the approval time is a function of the amount of transaction activity, seller registration volume and unrelated corporate activity. As a result, the time to approval is exogenous and random from the viewpoint of an individual seller.[11]

Taobao also provides a lot of information about its activities on its website. Specifically, it regularly posts the information on the number of buyers and sellers transacting at Taobao. In addition, it provides details on the total transaction volume. The website also carries a list of all available products, organized as a hierarchy of category, sub-category, etc. all the way to the individual item. Other supplementary data can also be obtained relatively easily at search engines such as baidu.com. Thus, sellers and buyers have access to quite a lot of information before they decide to join the platform. Taobao also advertised on TV during the 2003-2005 period to inform consumers about the existence of the platform - unfortunately, we do not have access to these data.

All transactions at Taobao are made via Alipay, which is linked to buyers and sellers' accounts in many banks in China. Using Alipay is free both for Taobao buyers and sellers. After a buyer

---

[10] Details on the seller registration procedure (in Chinese) are at http://service.taobao.com/support/8217702.htm?spm=0.0.0.0.HhGcmw.

[11] Note that as Taobao is a C2C platform, an agent can function as a buyer *and* a seller. If an agent registers as a buyer first, then s/he is counted as a seller only if s/he applies to be a seller and the application is approved. On the other hand, if an agent applies to be a seller first (and is approved), then s/he is counted as buyer only when s/he makes the first purchase. The marginal impact of the presence of such agents could be different from the impact of agents who are pure buyers or sellers in the evolution of the network. Taobao estimates that in general, the number of such agents (acting as both buyer and seller) is about 10% of all active sellers. So at the end of 2012, 700,000 of the 435 million buyers are also sellers and 7 million sellers are also buyers. We were also able to obtain more disaggregate data on three reasonably large product categories – women's shoes, diapers and cell phones. The number of sellers who acted as buyers in these three product categories was 0.15%, 0.24% and 0.17% in women's shoes, diapers/baby products and cell phones. Given the aggregate nature of our data, we cannot control for this potential difference explicitly. While this remains a limitation of our data, the relatively small proportion of such agents is unlikely to "contaminate" the average estimated effect in any significant manner.

places an order with a seller and pays Alipay, Alipay notifies the seller of the purchase and asks the seller to fulfill the order. The seller then arranges for logistics and delivery and notifies the buyer of shipping details (shipping date, expected delivery date, tracking information, etc.). Alipay holds the payment for one month or upon buyer's confirmation of delivery. The money paid to Alipay is held in escrow by a Chinese national bank. The funds held by Alipay are not available to Taobao for any use under Chinese regulation.

The free buying and selling policy means that Taobao does not earn money from buyer and seller registration and transaction. Taobao's revenues are based on three sources. The primary source is from seller online advertising expenditure on Taobao.com – this is operated and managed by www.etao.com (the entity that replaced the now dysfunctional www.alimama.com). The second source is seller participation fees in Taobao's special marketing channels and promotional activities, such as "Taobao Golden Coins," "Everyday Special Prices," "Trial Center," etc. The third source is fee-based shop management tools (such as software) and value-added services for sellers. Taobao estimates that there is the usual 80:20 split across sellers with approximately 20% of the sellers accounting for about 80% of the transactional revenue. Not surprisingly, the majority of Taobao's own revenue comes from this heavy seller group.

5. Data and Variable Operationalization

As noted earlier, our data are novel, especially in the sense that we have data from Taobao's inception. Specifically, we have daily observations from 5/11/2003, the day when the first seller registered on Taobao, to 12/31/2012. For each day, we observe the number of new buyers, new sellers, transacting buyers, transacting sellers, transactions, unique items sold, total items sold, mean transaction prices, expenditures per buyer, expenditure per transaction, and total revenues. These variables are aggregated across all products. At the product category level (Taobao defines its own product categories), we observe numbers of new items added, total number of items on shelf, mean item price, and total transactions for each product category.[12]

[12] Taobao also allows buyers to rate sellers on a 5 "star" scale. It is quite possible that buyers decide to join Taobao based on average seller ratings across the platform. We approached the company about getting data on ratings. The company did not provide us the ratings for the following three reasons. First, Taobao executives told us that, during this period, given the large number of transactions, only about 40% of them had actual ratings by buyers. For the remaining 60%, Taobao would assign them 5 stars (the maximum) as the default rating. Second, the average rating across all sellers on a daily basis did not have much variation. Third, Taobao had noticed that some buyers were using the Aliwangwang communication tool to "intimidate" sellers into

5.1 Data summary

Table 2 summarizes daily new sellers and new buyers, their annual totals and growth. During Oct to Dec 2003, the average number of new sellers and buyers on a day was 15 and 3 respectively. Daily new sellers reached three digits and daily new buyers reached four digits in 2004. The platform really started to take off in 2007 - nearly 3,000 sellers and 57,000 buyers registered each day, and over one million sellers and 20 million buyers registered in that year. The seller installed base reached two million and the buyer installed base exceeded 46 million. Since then, both buyer and seller numbers continued to grow. In 2012, there were 14,000 new sellers and 360,000 new buyers added to the platform each day. By the end of 2012, the installed base was 21 million (sellers) and 435 million (buyers). Note that this installed base here does not account for seller and buyer attrition (we discuss this in detail below).

Over time, the total number of transactions per day has gone from two thousand per day in 2004 to 13 million in 2012. Table 3 reports percentages of sellers and buyers with transactions over total sellers and buyers as well as total transactions per day. The share of sellers with a transaction has remained stable in the last three or four years at around 5% (around 11% once we account for seller attrition). On the other hand, the share of buyers making purchases has been rising slowly since 2006, culminating at about 1.4 out of 100 registered buyers making a purchase in end 2012.

Table 4 shows some characteristics of daily transactions, including mean item price, size of each transaction, and revenues. The daily transaction revenue has been increasing rapidly and reached 1.61 billion yuan (USD 258 million) in 2012. The average item price stabilized to around 13 yuan (USD 2.09) by 2006 after some initial fluctuation. The value of each transaction[13] has also stabilized to around 125 yuan (USD 20) with the expenditure per buyer being around 325 yuan (USD 52.17).

5.2 Variable operationalization

Due to the nature of the research methodologly, data and institutional setting, we need to construct many of the variables that we use. We discuss these below. In a subsequent section (6.3), we explore the robustness of our results to alternative operationalization of these variables.

giving them better deals in return for more favorable ratings, i.e., these ratings were not truly reflective of seller quality. Fourth, at a seller's request and provision of evidence that a certain rating is a result of buyer's (failed) intimidation attempt, Taobao can revise or erase bad ratings. These reasons suggest that aggregate ratings data were likely to be quite noisy and hence not particularly useful.

[13] This includes shipping fees that range from 1% to 15% of transaction size depending on product category. Generally the smaller the total basket value in yuan, the higher the percentage shipping fee.

5.2.1 Buyer and seller installed base

We use the cumulative sum of registered buyers each day as the installed base of buyers, and that of registered sellers each day as the installed base of sellers.[14] As noted earlier, Taobao's policy is that once a buyer activates his/her account, s/he remains a buyer, regardless of transaction activity. Unlike buyers however, Taobao has data on whether a seller is present and active on the platform. Sellers exit either voluntarily from the platform (typically for business reasons e.g., they are not profitable) or involuntarily (usually because they violate Taobao rules and regulations and the platform shuts them down). By Dec 31, 2012, the total number of sellers ever registered exceeded 21 million, but the total number of sellers in normal state (defined as transacting and/or engaging in merchandising activity at least once a quarter) was only 7.1 million, i.e., about one-third the cumulative sum of registered sellers. We therefore need to adjust the cumulative sum of registered sellers in order to be consistent with the number of sellers in the normal state.[15] Based on our discussion with the company, we assumed that sellers drop out in a manner consistent with an exponential decay. Specifically, if there are $n_{t-\tau}{}^S$ sellers registered at t-τ, by time t, there will be $n_{t-\tau}{}^S/(1+r^S)^\tau$ sellers left where r^S is the decay parameter. In order to estimate this parameter, we equate the predicted number of sellers (using this parameter) with the actual number of normal state sellers on Dec 31, 2014. The best-fit value for r^S is 0.0018, i.e., every day 1.8 out of 1000 sellers drop out (we test the robustness of the model estimates to this adjustment later in the paper). Figure 1 shows the buyer installed base and seller installed base (with and without the adjustment).

5.2.2 Product variety index

We first compute the platform's category concentration in the number of product items (equivalent to stock keeping unit). Analogous to the industry concentration Herfindahl-Hirschman Index (HHI),

[14] Given the modest transaction size, it is possible that transactions on Taoabo skew local i.e., buyers tend to buy from local sellers. In that case, both parties would care about the local installed base rather than the national installed base. We were able to obtain some supplemental data from Taobao.com vis-à-vis this issue. For the women's shoe product category, across China's 31 provinces, the average percentage of buyers *outside of a seller's province* is 92.01% (with a range of 29.26% to 100%). Taobao also reported to us that for the cellphone category, buying is nationwide (following the population distribution) while selling is concentrated with 80% of sellers based in Guangdong. This suggests that agent utility is based on the national installed base, not a local one. In fact, feedback from the company's surveys suggests that sellers wanted to go online at Taobao because it gave them access to a national market of buyers (as opposed to a local market for a physical store) – virtually no sellers on Taobao maintain a physical store. Buyers on the other hand went on Taobao to get the best prices from sellers nationwide.

[15] The company was unable to provide us an exact count of the number of normal sellers on each day due to the cost involved in extracting these data.

category c's share in the number of items is $S_t^c = I_t^c / I_t$, where I_t^c is the number of items in category c and I_t is the number of items across all product categories. The category's item concentration HHI is calculated as:

$$HHI_t = \sum_{c=1}^{C} (S_t^c)^2$$

Product variety index is defined as $V_t = 1 - HHI_t$. V_t lies between [0, 1]. When all items are concentrated in one category, $V_t = 0$, and when all items are evenly distributed across categories, $V_t = 1 - 1/C$. V_t approaches 1 when the number of categories increases. Similar index is used to measure variety in other studies (e.g., Fan 2013). Product variety at Taobao has been increasing. It fluctuates substantially in the beginning years and gradually stabilizes at a high level.

5.2.3 Buyer quality

We define buyer quality as the number of transactions per 100 buyers in the installed base, calculated by dividing the number of transactions each day by the installed base of buyers (x100). This is an indicator closely monitored by the platform. It is also highly relevant for the platform's current strategic focus. We test the sensitivity of model parameter estimates to other measures of buyer quality. The right most columns of Table 3 report the average daily buyer quality and its standard deviation for each year. Most Taobao buyers are not active. On an average day, there are only 2.5 transactions per 100 buyers. Even during the peak promotion days such as "Double 11" (November 11) and "Double 12" (December 12) promotions, the number of transactions is still less than 10 per 100 buyers. However, buyer quality has been gradually improving over the years.

5.2.4 Product price

We take a representative consumer approach in the model setup. We observe the average transaction prices across all items for each day. For sellers, we can use this price because sellers are assumed to be more informed of product prices.[16] However, using average prices for a representative buyer is equivalent to requiring her to know prices in each product category, which is too strong an assumption. Instead, we construct a price index using a fixed basket. We compute basket shares based on the total revenues of the fifty categories that are sold throughout the entire

[16] We do not adjust prices for inflation in our main model. We did run a model with adjusted prices and the correlation between the reported results and the one with the inflated adjusted prices is 0.99. Relative to the initial period, i.e., over a ten-year period, the CPI went up 37%. The monthly (and hence daily movement) in CPI is therefore relatively very small, resulting in it not having a meaningful impact on the results (which are available from the authors on request).

period, and compute price index using the basket shares. We check the robustness on the number of categories included, and on fixed basket versus time-varying basket. Over the years, average basket prices have been declining to within 200 yuan (USD 32), corroborating Taobao's low-price image.

5.2.5 Seasonal, promotional event and holiday controls

Taobao started "Double 11" and "Double 12" promotions from 2010. Ever since, these two days have become the biggest promotional activities for the platform and for its buyers and sellers as well. We create dummies for these two days.

Many households in China may not have computers with Internet access at home. They often surf the web from offices. They may have more engagements on weekends, such as visiting friends, shopping at physical stores, or simply relaxing. We create a dummy for each day of the week to account for these effects.

Many holidays in China run over several days, some for even a week or more. Logistics companies nearly stop operations during these holidays, particularly during the Lunar Chinese New Year, which greatly hinders online shopping behavior. We create dummies for all Chinese holidays to capture these effects.

6. Estimation

We use maximum likelihood to estimate the model parameters. In the estimation, we need to address two issues, one is how the market for buyers and sellers evolve over time, and the other is how to resolve the potential simultaneity and endogeneity of the buyer's and seller's installed bases.

6.1 Potential market sizes for buyers and sellers

We allow buyers and sellers to have the option of not joining the platform. We use the number of Internet users in China as the base of the potential market for buyers and scale it by 1.3 because an average buyer has 1.3 accounts at Taobao.[17] Buyer's market size evolves as follows: At the beginning of time t, there are M_t^B buyers. During time period t, n_t^B buyers join the platform and drop out of the market, and there are m_t^B new Internet users joining the potential market. At the end of time t (or beginning of time t+1), the market size is $M_{t+1}^B = M_t^B - n_t^B + m_t^B = M_t^B\,(1 - z_t^B)$.

The great majority of Taobao sellers are individual entrepreneurs, and it is quite common for

[17] The data on the number of Internet users in China is obtained from the China Internet Network Information Center (CNNIC). Internet usage in China has grown rapidly over the last decade. In June 2003, there were 68 million Internet users with a penetration rate of 5.6%. By December 2012, there were 564 million Internet users with a penetration rate of 42.1%.

wife and husband to start a Taobao business, either full time or part time. Therefore, we use the number of households in China as the base of the potential market for sellers. Based on internal surveys carried out by Taobao, we scale this by 0.1, with the assumption being that the potential number of sellers for Taobao is likely to be a maximum of 10% households.[18] From May 2003 to December 2012, households in China increased from 374 million to 448 million. Seller's market size evolves as follows: At the beginning of time t, there are M_t^S sellers. During time t, n_t^S sellers join the platform and drop out of the market, and there are m_t^S households joining the potential market. At the end of time t (or beginning of time t+1), the market size becomes $M_{t+1}^S = M_t^S - n_t^S + m_t^S = M_t^S (1 - z_t^S)$.

6.2 Potential simultaneity and/or endogeneity

Some common unobservables may affect buyer's and seller's decisions to join the platform. As buyer's and seller's installed bases are respectively cumulative sum of daily registered buyers and sellers, they might be correlated with the error term, causing the potential simultaneity/ endogeneity problem. Ordinary least squares will lead to biased estimates. We use the exclusion conditions, instrumental variables (IV) techniques, and control function approach to resolve this problem.

6.2.1 Exclusion restrictions

We find variables that affect only one side of the platform. Buyer quality affects seller's utility of joining the platform, but not buyer's utility of joining, because buyer quality directly affects seller's profits. On the other hand, product variety affects buyer's, not seller's propensity to join the platform because it increases the chance of product match for buyers. Previous studies (e.g., Boatwright and Nunes 2001, Briesch, Chintagunta and Fox 2009, Sun, Rajiv and Chu 2014) have found that product variety affects buyer's purchase, store choice or platform choice behavior.

Another exclusion restriction utilizes the specific institutional arrangements at Taobao, that is, the immediacy of buyers and sellers affecting the other side of the platform after registration (see Section 4). According to Taobao's regulations and requirements, buyers can make purchases immediately after registration approval (typically on the same day or occasionally the next day). Thus sellers can see the buyer installed base contemporaneously or at worst, with a one day lag. In our model, we assume that sellers are affected by the same day installed base of buyers i.e, $N_{t-\kappa}^B$, $\kappa =$

[18] Data on the number of households over time in China is from the State Statistics Bureau of China.

0. On the other hand, after registration, sellers need to get the platform's verification and approval and also need to carry out merchandising activities. Thus the installed base of sellers on buyers has a longer time lag ranging from two to seven days. In our model, we take the mid point of this interval i.e., $N_{t-\tau}^S$, $\tau = 4$.

6.2.2 Instrumental variables

Taobao buyers and sellers essentially come from the same population. Thus it is a big challenge to find instruments that affect one side, but not the other side of the market. Since many buyers buy from the platform because offline prices are too high, we use China's consumer price index (CPI), obtained from the State Statistics Bureau of China, and their lags as instruments for buyer's installed base. We particularly checked with the State Statistics Bureau that China's CPI does not factor in online purchases.

Similarly, we find instruments that only affect seller's propensity to join the platform, and thus the seller's installed base. We use the component indices of China's purchasing managers' index (PMI), including stocks of raw materials index, stocks of finished goods index, new orders index, manufacturer buying price index, suppliers' delivery time index, backlogs of work index, and procurement quantity index as instruments for sellers. These indices measure the difficulty, speediness and costs for sellers to obtain goods for online sales. These data are obtained from China Federation of Logistics and Purchasing (www.chinawuliu.com.cn) and the Hong Kong Shanghai Banking Corporation (www.hsbc.com/news-and-insight/emerging-markets). Further, households may open a shop at the platform as a way of investment, so we also use China's stock index as instruments, obtained from Shanghai Stock Exchange (http://english.sse.com.cn/).

6.2.3 Control function approach

Using the exclusion restriction and the instrumental variables, we take the control function approach (Petrin and Train 2010) to address the potential simultaneity / endogeneity problem. Specifically, we regress the buyer's installed base on China's CPI (with lags) and other exogenous variables and compute the regression residuals r_t^B (the first-stage R^2 is 0.89); we regress the seller's installed base on China's PMI component indices, stock index and other exogenous variables and compute regression residuals r_t^S (the first-stage R^2 is 0.82). We then put functions of the residuals back into the relative market share functions (equations (5) and (10)), as are shown in Equations (11) and (12), and re-estimate the model parameters. The control function includes both the linear and the quadratic term of the residuals (the results are also robust to other forms of control functions, i.e. only the linear term or only the quadratic term).

$$\ln(\frac{z_t^B}{z_t^{B,0}}) = \beta_0 + \beta_{1\bar{t}} \ln(N_{t-\tau}^S) + \beta_2 \ln(p_t) + \beta_3 V_t + \beta_4 X_t + \beta_5 CF(r_t^S) + \xi_t^B \tag{11}$$

$$\ln(\frac{z_t^S}{z_t^{S,0}}) = \alpha_0 + \alpha_{1\bar{t}} \ln(N_{t-\kappa}^B) + \alpha_2 \ln(p_t) + \alpha_3 Q_t^B + \alpha_4 X_t + \alpha_5 CF(r_t^B) + \xi_t^S \tag{12}$$

The econometric error terms ξ_t^B and ξ_t^S might be correlated. We assume they follow bivariate normal distribution as in Equation (13) and estimate model parameters jointly via the maximum likelihood method.

$$\begin{pmatrix} \xi_t^B \\ \xi_t^S \end{pmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^{B2} & \rho\sigma^B\sigma^S \\ \rho\sigma^B\sigma^S & \sigma^{S2} \end{bmatrix} \right) \tag{13}$$

6.2.4 Measurement of cross-network effect and non-network effect

Following the literature (e.g., Gandal et al. 2000), we use elasticities to measure CNE. We compute the impact on the number of buyers (sellers) when seller's (buyer's) installed base increases by 1%. The equations to compute cross-network elasticities are as follows:

$$\begin{aligned} e_{S2B} &= \beta_{1\bar{t}}(1 - z_t^B) \\ e_{B2S} &= \alpha_{1\bar{t}}(1 - z_t^S) \end{aligned} \tag{14}$$

The equations to compute the effect of product price are as follows:

$$\begin{aligned} e_{S2B,p} &= \beta_2(1 - z_t^B) \\ e_{B2S,p} &= \alpha_2(1 - z_t^S) \end{aligned} \tag{15}$$

The equation to compute elasticities for the effect of product variety index on buyers is:

$$e_{S2B,V} = \beta_3 V_t (1 - z_t^B) \tag{16}$$

The equation to compute elasticities for the effect of buyer quality on sellers is:

$$e_{B2S,Q} = \alpha_3 Q_t^B (1 - z_t^S) \tag{17}$$

7. Results

In this section, we first present the main parameter estimates and then explore the implications of the overall results for managers.

7.1 Parameter estimates

7.1.1 Cross-network effects

Even though the platform was open for transactions in May 2003, there were very few transactions till Nov 2003. We therefore use data from Nov 2003 to Dec 2012 for our estimation (this also allows for the use of lagged variables without the initial condition problem). To capture the evolution of CNEs over time, we interact the installed base with year and month dummies (11/2003-12/2012). Thus, we have 110 coefficients for the buyer installed base and 110 for the seller installed base. All the cross-network coefficients are statistically significant (the mean t-statistic for the buyer equation is 18.35 with a standard deviation of 1.91 and that of the seller equation is 21.78 with a standard deviation of 4.72). The evolution of the CNEs is shown in Figure 2a. We now discuss three aspects of these results in detail.

First, there exists a large, significant and positive CNE on both sides of the platform, indicating that the installed base of either side of the platform has propelled the growth of the other side. Specifically, we find that when the installed base of sellers increases by 1%, the number of new buyers will on average increase by 1.51% (sd = 0.14%, min = 1.36%, max = 1.81%); when the installed base of buyers increases by 1%, the number of new sellers will on average increase by 0.42% (sd = 0.04%, min = 0.26%, max = 0.49%). Our finding of significant positive CNEs on the C2C online platform is analogous to the findings in other settings such as Yellow Page (Rysman 2004) and magazines (Kaiser and Wright 2006, Song 2013). However, the magnitudes of these effects are much larger in the online C2C platform than in these other settings. The mutually enhancing CNEs imply that in the introduction stage, the platform needs to take necessary measures, e.g., free or subsidized pricing, to encourage the growth of the installed base. They also imply that once the installed bases become large enough, the positive externalities will accelerate the growth on both sides without too much intervention from the platform.

Second, the CNE is asymmetric. The seller installed base has a much larger impact on buyer growth than vice versa. This suggests that the platform is much more seller driven than vice versa, especially in the early stages. In Figure 2b, we plot the ratio of seller's cross-network externality on buyers over buyer's cross-network externality on sellers. On average, seller's CNE is 3.63 times as large as buyer's CNE, ranging from 2.81 to 6.66. This ratio declined over time, at a faster speed in the initial two years, which was primarily driven by the decreasing seller's CNE. The ratio started to stabilize around 3.1 from 2010. This asymmetry in the CNE implies that a more preferential policy for the side (sellers) with a larger CNE will be more effective for the platform's growth than the other way around (Rochet and Tirole 2003, Armstrong 2006).

Third, the buyer's CNE on sellers is relatively stable over time. On the other hand, the seller's CNE on buyers, first increases (2003-2004) and then decreases (from mid-2005). It becomes stable after 2010. Thus, it appears that in the introduction phase, the platform's growth is primarily seller-driven: seller growth induces buyers to register, which in turn leads to more sellers to register, which further encourages more buyers to register, etc. In the growth stage, the seller's CNE is declining, but it is still well above the buyer's CNE.

7.1.2 Non-network factors

In addition to cross-network externalities, non-network factors such as product variety, product price, and buyer quality also contribute to the growth of the platform. In Table 5, we report the parameter estimates of non-network factors, respectively for OLS, separate 2SLS and joint 2SLS.

As can be seen from the table, product price does not have a significant effect on buyer growth. This might be because Taobao has been positioned as a low-price platform from the very beginning and has successfully established this price image. In addition, based on our discussion with Taobao managers, it turns out that absolute price levels may not matter much as long as Taobao has lower prices than other options, typically physical stores. In contrast, product price does affect seller growth in a significant manner. Specifically, a 10% increase in product price will lead to 0.7% increase in sellers. Sellers do care about price levels as they affect their profits directly.

Product variety has a large, significant and positive effect on buyer growth, next only to the CNE. When the product variety index increases by 1%, new buyers will increase by 1.13% (sd = 0.07%). Besides the large installed base of users (buyers and sellers), product variety is another biggest differentiator between Taobao and all other retailing channels. Many consumers patronize Taobao because they can buy nearly everything there ("Taobao" literally means "treasure hunt" in Chinese). As Taobao's positioning catchphrase goes, "there is no treasure that cannot be hunted out" in Taobao. Thus, it may not be surprising that product variety has a large effect on buyer growth.

Buyer quality has a significant and positive effect on seller growth. When buyer's quality increases by 10%, new sellers will grow by 0.8% (sd = 0.5%). Given the buyer installed base, when buyers make more transactions, it definitely increases the platform's attractiveness to sellers. Since seller growth will lead to more buyers, it is important for the platform to take measures to induce buyers to transact more at the platform.

Most holidays have a significant dampening effect on buyer and seller growth, particularly the latter. Interestingly, sellers are more responsive to holidays and seller registrations go down dramatically on all holidays. Buyer registrations go down substantially during the Chinese Lunar New Year, the National Day, and the Labor Day and do not change much during other holidays. The deepest drop occurs on the Chinese Lunar New Year when new seller registrations are 48.3% lower and new buyer registrations are 28.2% lower than other days. China's National Day Holiday is another low day with seller registrations going down by 32% and buyer registrations down by 12%.

Buyers are mostly likely to register on Monday, followed by Tuesday and Friday and least likely to register on weekends. There are 7.4% more buyer registrations on Monday and 5% more on Tuesday and Friday than on Sunday. Sellers are mostly likely to register on Tuesday through Thursday, followed by Monday and Friday, and least likely to register on weekends. There are 15% more seller registrations on Tuesday through Thursday, and 10% more on Monday and Friday than on Sunday.

The "Double 11" promotion has a large and significant impact on buyer growth, but a large and significant negative impact on seller growth. On that day, buyer registrations increase by 73% because buyers want to take advantage of Taobao's biggest price promotions in a year. On the other hand, seller registrations decrease by 15%. This is because it takes several days for seller registration to be verified and approved and sellers thus advance their registrations so they can sell on the biggest promotion day. Surprisingly, the "Double 12" promotion does not significantly affect buyer and seller registration. One reason might be that it is too close or not far enough from the "Double 11" Promotion, and both buyers and sellers have not fully absorbed the previous promotional effect.

7.1.3 Relative contribution of network and non-network factors

To compare the relative contributions of network and non-network factors to the platform's development, we compare the relative magnitudes of their elasticities in the growth of new buyers and new sellers. Gandal, Kende and Rob (2000) use a similar approach to compare the relative effectiveness of hardware price cuts versus software provision in driving hardware adoptions. For buyer growth, we focus on two factors, seller installed base and product variety; for seller growth, we focus on three factors, buyer installed base, buyer quality, and product price.

In Figure 3a, we plot the evolution of network and non-network effects on the growth of buyers. Through the platform's entire history, the network factor has been the primary driving force for buyer's growth. However, its effect is declining gradually. Product variety, on the other hand, is exercising increasing influence in buyer growth. The decomposition of the two effects show that, by Dec 2012, the CNE accounts for 60% of the growth with the balance coming from product variety.

In Figure 3b, we plot the evolution of network and non-network effects on the growth of sellers. Similarly, network factor has been the dominant force for seller's growth. However, its effect is declining over the platform's lifecycle. The effect of product price is relatively stable. Buyer quality, on the other hand, has a growing impact over time. In the first half of the data period, buyer quality is the third important factor, lower than product price, while in the second half of the period, it rises to be the second important factor, exceeding the impact of product price.

The finding of declining network effect is at variance with that in the U.S. video game console market where expanding software variety (cross-network effect) becomes more effective over time (Clements and Ohashi 2005) as well as in the PDA market (Nair et al. 2004) where software provision has a growing effect on hardware adoption. This difference may be due to the fact that we focus on platforms (where the intermediary does not produce or own any goods) and/or the fact that we model non-network factors explicitly and/or due to the specific institutional setting in our study (Internet commerce, Chinese market, etc.).

7.2 Robustness checks

We conduct a series of robustness checks, including the scale factor for buyer's and seller's potential market sizes, the discount factor for seller's installed base, the period of lags for seller's and buyer's installed base, (no) instrumental variables and their lags, and definition of buyer quality. In the interest of brevity, we do not report the results of these robustness checks in the paper. However, they are available from the authors on request.

7.2.1 Scale factors for the potential market size

We tried different scale factors for the buyer and seller potential market size (see Section 5.2.1). For the buyer potential market size, we used a scale factor of 1, 1.5 and 2 (we use 1.3 in the main model). For the seller potential market size, we used a scale factor of 0.05, 0.20 and 1 (we use 0.1 in the main model). We find the change of scale factors only shifts the intercepts up or down and does not affect the estimates of other parameters much (this is consistent with previous work, see Chu and Chintagunta 2009, Chu 2013).

7.2.2 Discount factor for the seller installed base

We also estimated our model without adjusting for the difference between registered sellers and normal state sellers (see Section 5.2.1). In other words, we use cumulative sum of all registered sellers as the seller installed base. We find that this affects only the estimate of the intercept. There is no material change in the other coefficients.

7.2.3 Buyer and seller registration approval duration

As noted in Section 6.2.1, there is a difference in how quickly buyer registrations and seller registrations are approved by Taobao. We have used zero days for buyers to appear in the installed base for sellers to consider and four days for sellers to appear in the seller installed base for buyers to consider. We estimated our model with different approval times spanning the entire range of times. Specifically, for buyers, we looked at a one day approval and for sellers we looked at two, three, five, six and seven day approval. We find that our estimates are not sensitive to the choice of approval period.

7.2.4 Measurement of buyer quality

Recall that we used the number of transactions per 100 buyers in the installed base as a measure of buyer quality (Section 5.2.2). We also used alternative measures of buyer quality - the number of transactions per transacting buyer and the percentages of transacting buyers in the installed base. We obtained similar results on the network factors and non-network factors.

7.2.5 Instrumental variables

First, we estimated our model while omitting the instrumental variables and thus omitting the control functions in Equations (11) and (12). Second, we tried different lags of the instrumental variables. Third, we tried different instruments, such as the unemployment index for the seller's installed base in acknowledgement of the fact that many sellers are individual entrepreneurs and Taobao is China's largest employer (direct and indirect via other related industries such as logistics and warehousing). In each case, we found quantitatively similar results.

7.2.5 Including time trends

We do not explicitly include time trends in our model. In this robustness check, therefore, we add a time trend and a time trend squared term to both buyer and seller utility. However, once we include these terms, the time varying CNEs are not identified. So we estimate the model with static CNEs. The main difference in the results from such a model and the reported estimates is that the CNE of sellers on buyers goes up to 2.38 (as opposed to approximately 1.51 in steady state). The CNE of buyers on sellers is estimated to be 0.44 (virtually identical to the steady state estimate of approximately 0.42). Thus, our reported CNE of sellers on buyers is a conservative estimate.

7.2.6 The role of initial conditions

The early years of Taobao were characterized by a slightly different competitive situation (see Section 4) and fluctuations in the average item price and transaction value. In order to make sure that our steady-state estimates were not affected by these factors, we re-estimated the model for two data periods – 2003-2005 and 2006-2012. We find that the estimated CNEs do not differ significantly, especially for the latter period.

7.3 Managerial implications

Managers of platforms are typically concerned with understanding the primacy of one side versus the other. If they know the size and asymmetry in the CNEs, they can allocate resources more efficiently. In addition, they can also try and influence factors that are more under their control. We focus on two such factors - product variety and buyer quality – to show the impact that changes in these two factors can have on the growth of the network. We also discuss qualitatively the impact of our findings on Taobao's practices.

7.3.1 Changes in product variety

Changes in product variety have both direct effect and indirect effect. Since buyers value product variety, a deterioration (an improvement) in product variety will lead to fewer (more) new buyers to register on the platform. This is the direct effect. Fewer (more) buyer registrations will reduce (increase) *buyer*'s installed base in all future periods, which will discourage (encourage) new *sellers* to register, which will decrease (increase) *seller*'s installed base in all future periods, which will lead to fewer (more) new *buyers*. This forms the indirect effect. On the other hand, although seller registrations are not directly affected by changes in product variety, they will be indirectly affected by the resultant changes in buyer installed base brought by changes in buyer registrations.

We disentangle the direct and indirect effects of a change in product variety using two scenarios. In the first scenario, we fix the buyer and the seller installed bases at their observed values in the data (direct effect), and in the second, we allow buyer and seller installed bases to change in the future by responding to changes in new buyer and new seller registrations. For each scenario, we simulate new buyers and new sellers using the cross-network parameter estimates and non-network parameter estimates reported in Table 5 and compute the corresponding buyer's installed base and seller's installed base for each day from 11/1/2003 to 12/31/2012. The first scenario does not account for the changes in new buyers and new sellers brought by the changed seller and buyer installed bases, so it measures the effect of product variety changes net of network effect. The second scenario allows sellers to respond to changes in the buyer installed base, and buyers to respond to changes in seller's installed base, so it measures the total effect, i.e., direct and indirect effects of product variety. The difference between these two scenarios can be taken as the effect of installed base, or CNE.

We simulate the effect of reducing product variety by setting product variety level to zero, which is akin to forcing all products sold on Taobao to be in one category. In Figure 4, we plot the ratio of simulated seller installed base over observed seller installed base for the scenario without network effect and the scenario with network effect, as well as the ratio of simulated buyer's installed base over observed buyer's installed base for these two scenarios.

Several observations are in order. First, minimizing product variety will substantially discourage buyer and seller registrations, leading to considerable reductions in buyer and seller installed bases. The buyer installed base without any product variety would be only about 10% of the actual buyer installed base, and the seller installed base would be around 40% of the actual seller installed base. Second, the CNE compounds the effect of product variety, both on buyers and sellers. The simulated buyer installed base would be around 35% of the actual installed base, if there were no CNEs, as compared to around 10% with CNEs. Since product variety does not directly affect seller registration, the reduction in seller's installed base is totally due to CNEs. Third, product variety has a much larger impact on buyers than on sellers, both directly and indirectly. The buyer installed base would be much more negatively affected by reducing product variety than the seller installed base.

7.3.2 Changes in buyer quality

Similarly, changes in buyer quality have both direct effect and indirect effect. Since sellers value buyer quality, an increase in buyer quality will lead to more new sellers to register on the platform. This is the direct effect. More seller registrations will increase the seller installed base in all future periods, which will encourage new buyers to register, which will increase buyer's installed base in all future periods, which will lead to more new sellers. This forms the indirect effect. On the other hand, although buyer registrations are not directly affected by changes in buyer quality, they will be indirectly affected by the resultant changes in seller's installed base brought on by changes in seller registrations.

The direct and indirect effects of a change in buyer quality can also be disentangled in the same way as the change in product variety. We simulate the effect of doubling buyer quality. In Figure 5, we plot the ratio of the simulated seller installed base over observed seller installed base for the scenario without network effect and the scenario with network effect, as well as the ratio of the simulated buyer installed base over the observed buyer installed base for these two scenarios.

We observe the following. First, enhancing buyer quality will encourage sellers and buyers to register, leading to sizable increases in the seller and buyer installed bases. The seller installed base would be nearly 20% higher than the actual seller installed base, with increasing effect over time; the buyer installed base would be at least 20% higher than the actual installed base, with cyclical effect over time. Second, CNE compounds the effect of buyer quality, both on sellers and buyers. The simulated seller installed base would be about 10% higher than the actual installed base, if there were no CNE, as compared to nearly 20% higher with CNEs. Since buyer quality does not directly affect buyer registration, the increase in buyer installed base is completely due to CNEs. Third, although buyer quality does not affect buyer registration directly, it has a larger impact on buyers than on sellers, except for the beginning month. This is because the seller installed base has a much larger effect on buyers than vice versa, and the CNE on buyers outweighs the direct effect of buyer quality on sellers.

7.3.3 Impact at Taobao

We shared our analysis and findings with Taobao. One aspect of their reaction is particularly noteworthy. The generally held wisdom in the company was that buyers were more important than sellers as they had a bigger impact on sellers rather than the other way around. Our finding – that the seller on buyer CNE was 3.5 times as big as the CNE of buyer on seller was seen as a very surprising finding. In a separate conversation with Savio Kwan, the ex-COO of the Alibaba group, we discovered the reason for this view. He noted that in the early days of Taobao, the belief was that buyers had the purchasing power and hence needed to be nurtured over sellers (who were after all making profits and so were getting rewarded for participating on the platform). This belief had become rooted in company culture over time.

As a result of our findings, the company's managers started to become more "seller friendly." They lowered the emphasis on seller ratings and generally focused on improving seller welfare. In addition, they started exploring mechanisms to reactivate buyers (via targeted emails) in order to improve buyer quality. To improve product variety, on the margin, they encouraged sellers who provide more variety (relative to what was already available on the platform).

8. Conclusion

This paper adds to the small but growing empirical literature on platforms (or two-sided markets), especially in online settings. We use novel data that span the entire history of the world's largest C2C platform – Taobao in China – to model its growth. Specifically, we take a structural approach to track the growth as a function of network and non-network factors. We focus on the quantification of the CNEs over the platform's lifecycle and compare the relative importance of network and non-network factors in the platform's growth. We find a large, significant and positive CNE on both sides of the platform market, but the CNE is asymmetric with the installed base of sellers having a much larger effect on the growth of buyers than vice versa. The growth in the number of buyers is driven primarily by the seller installed base and product variety with increasing importance of product variety. In contrast, the growth in the number of sellers is driven by the buyer installed base, buyer quality, and product price with increasing importance of buyer quality. We further find that the CNE of sellers on buyers increases and then decreases to reach a stable level. In contrast, the CNE of buyers on sellers is relatively stable. Finally, we carry out analyses to show how increasing product variety and buyer quality have a material direct and indirect effect on the installed base.

Our paper suffers from a few limitations, mostly driven by the nature of the available data. First, our measures of price and product variety are aggregates across the platform. Second, we cannot control for differences across buyers and sellers given the lack of individual level data. Third, we assume that both sellers and buyers are myopic in their decision to join the platform. In the Taobao setting, this is perhaps not a first-order issue because the platform's free-pricing policy together with nearly hassle-free registration greatly reduces sellers' and especially buyers' risk of joining and transacting on the platform and thus their incentives to look forward. We hope that future research can address these limitations.

References

Ackerberg, Daniel A. and Gautam Gowrisankaran. 2006. "Quantifying Equilibrium Network Externalities in the ACH Banking Industry," *RAND Journal of Economics*, 37(3), 738-761.

Argentesi, Elena and Lapo Filistrucchi. 2007. "Estimating market power in a two-sided market: The case of newspapers," *Journal of Applied Econometrics*, 22(7), 1247-1266.

Armstrong, Mark. 2006. "Competition in Two-Sided Markets," *RAND Journal of Economics*, 37(3), 668-691.

Boatwright, Peter and Joseph C. Nunes. 2001. "Reducing Assortment: An attribute-based approach," *Journal of Marketing*, 65(3), 50-63.

Briesch, Richard A., Pradeep K. Chintagunta, and Edward J. Fox. 2009. "How Does Assortment Affect Grocery Store Choice?" *Journal of Marketing Research*, 46(2), 176-189.

Caillaud, Bernard and Bruno Jullien. 2003. "Chicken and Egg: Competition among Intermediation Service Providers," *RAND Journal of Economics*, 34, 309-328.

Chandra, Ambarish and Allan Collard-Wexler. 2009. "Mergers in Two-Sided Markets: An Application to the Canadian Newspaper Industry," *Journal of Economics & Management Strategy*, 18(4), 1045-1070.

Chen, Yuxin and Jinhong Xie. 2007. "Cross-market Network Effect with Asymmetric Customer Loyalty: Implications for Competitive Advantage," *Marketing Science*, 26(1), 52-66.

Chu, Junhong and Pradeep K. Chintagunta. 2009. "Quantifying the Economic Value of Warranties in the U.S. Server Market," *Marketing Science*, 28 (1), 99-121.

Chu, Junhong. 2013. "Quantifying Nation Equity with Sales Data: A Structural Approach," *International Journal of Research in Marketing*, 30(1), 19-35.

Clements, Matthew T. and Hiroshi Ohashi. 2005. "Indirect Network Effects and the Product Cycle: Video Games in the U.S., 1994-2002," *Journal of Industrial Economics*, 53(4), 515-542.

Dubé, Jean-Pierre H., Günter J. Hitsch, and Pradeep K. Chintagunta. 2010. "Tipping and Concentration in Markets with Indirect Network Effects," *Marketing Science*, 29(2), 216-249.

Fan, Ying. 2013. "Ownership Consolidation and Product Characteristics: A Study of the US Daily Newspaper Market", *American Economic Review*, 103(5), 1598-1628.

Gandal, Neil, Michael Kende and Rafael Rob. 2000. "The Dynamics of Technological Adoption in Hardware/Software Systems: The Case of Compact Disc Players," *RAND Journal of Economics*, 31(1), 43-61.

Jin, Ginger Zhe and Marc Rysman. 2012. "Platform Pricing at Sports Card Conventions," Working Paper, University of Maryland.

Kaiser, Ulrich and Julian Wright. 2006. "Price structure in two-sided markets: Evidence from the magazine industry," *International Journal of Industrial Organization*, 24, 1-28.

Liu, Hongju. 2010. "Dynamics of Pricing in the Video Game Console Market: Skimming or Penetration?," *Journal of Marketing Research*, 47(2), 428-443.

Nair, Harikesh, Pradeep Chintagunta, and Jean-Pierre Dubé. 2004. "Empirical Analysis of Indirect Network Effects in the Market for Personal Digital Assistants," *Quantitative Marketing and*

Economics, 2, 23-58.

Ohashi, Hiroshi. 2003. "The Role of Network Effects in the US VCR Market, 1978-1986," *Journal of Economics & Management Strategy*, 12(4), 447-494.

Pattabhiramaiah, Adithya, S. Sriram and Hari Sridhar. 2013. "Rising prices under declining preferences: the Case of the U.S. Print Newspaper Industry," Working Paper, University of Michigan.

Park, Sangin. 2004. "Quantitative Analysis of Network Externalities in Competing Technologies: The VCR Case," *Review of Economics and Statistics*, 86(4), 937-945.

Petrin, Amil, and Kenneth Train. 2010. "A Control Function Approach to Endogeneity in Consumer Choice Models," *Journal of Marketing Research*, 47, 3-13.

Rochet, Jean-Charles and Jean Tirole. 2003. "Platform Competition in Two-sided Markets," *Journal of the European Economic Association*, 1(4), 990-1029.

Rochet, Jean-Charles and Jean Tirole. 2006. "Two-Sided Markets: A Progress Report," *RAND Journal of Economics*, 37 (3), 645-667.

Rysman, Marc. 2004. "The Economics of Two-Sided Markets," *Journal of Economic Perspectives*, 23 (3), 125-143.

Rysman, Marc. 2009. "A Study of the Market for Yellow Pages," *The Review of Economic Studies*, 71 (2), 483-512.

Seamans, Robert and Feng Zhu. 2014. "Responses to Entry in Multi-Sided Markets: The Impact of Craigslist on Local Newspapers," *Management Science*, 60(2), 476-493.

Shankar, Venkatesh and Barry L. Bayus. 2003. "Network Effects and Competition: An Empirical Analysis of the Home Video Game Industry," *Strategic Management Journal*, 24(4), 375-384.

Song, Minjae. 2013. "Estimating Platform Market Power in Two-Sided Markets with an Application to Magazine Advertising," Working Paper, University of Rochester.

Sriram, S., Puneet Manchanda, Mercedes Esteban Bravo, Junhong Chu, Liye Ma, Minjae Song, Scott Shriver and Upender Subramanian. 2013. "Platforms: A Multiplicity of Research Opportunities," *Marketing Letters*, forthcoming.

Sun, Li, Surendra Rajiv and Junhong Chu. 2014. "Variety and Superstar Effects in Two-Sided Markets," Working Paper, National University of Singapore.

Wang, Helen H. 2012. *The Chinese Dream: The Rise of the World's Largest Middle Class and What It Means to You*, 2nd ed., Bestseller Press, Chapter 7.

Wilbur, Kenneth C. 2008. "A Two-Sided, Empirical Model of Television Advertising and Viewing Markets," *Marketing Science*, 27(3), 356-378.

Appendix A: Direct Network Effects

The focus of our analysis is on the two cross network effects. However, direct network effects can influence platform growth as well. In other words, the installed base of buyers (sellers) has an impact on the utility of an individual buyer (seller). However, in our setting, these direct network effects are likely to be not very relevant. We discuss this in detail below for both the buyer and seller sides.

Direct Network Effect: Seller

From a seller's perspective, the installed based of sellers could lower his/her utility of joining due to the "congestion" effect. The congestion effect arises from the fact that as the seller installed base become bigger, the level of competition in the product category goes up. This is hard to test at the aggregate level. However, we were able to obtain summary data at the product category level (for sellers) for 96 product categories (as defined by Taobao).

In order to test for the existence and magnitude of the congestion effect, we ran the following regression to test for category-specific evidence of congestion (note that a significant and negative value of $\gamma_{1,c}$ represents evidence of congestion).

$$\ln(T_t^c) = \gamma_{0,c} + \gamma_{1,c}\ln(N_t^{c,S}) + \gamma_{2,c}\ln(N_t^{\bar{c},S}) + \gamma_3\ln(N_t^B) + \gamma_4\ln(p_t^c) + \gamma_5\ln(p_t^{\bar{c}}) + \gamma_6 X_t + \xi_t^c \qquad \text{(A1)}$$

Where, T_t^c is the number of transactions of category *c* at day *t*, $N_t^{c,S}$ is the number of sellers in category *c*, $N_t^{\bar{c},S}$ is the number of sellers in all other categories except for *c*, N_t^B is the installed base of buyers, p_t^c is category *c*'s mean price, $p_t^{\bar{c}}$ is the mean item price of all other categories except for *c*, and X_t is a vector of other transaction drivers, including all Chinese holidays, "Double 11" and "Double 12" promotions, and weekday dummies

We found evidence for congestion in six out of 96 categories (in the interest of brevity, we only discuss the relevant results). The effect size was large (elasticity greater than 1) for only two out of the six product categories (memory card/portable drive and 2nd-hand cars). These categories are relatively small in terms of transaction revenues, accounting for 0.035% and 0.008% of Taobao's revenue. The remaining four categories show statistically significant but very small congestion effects (see the table below), and only one of them is a relatively large category.

Category	$\gamma_{1,c}$	SE	t-stat	% Revenue
Memory card, portable drive	-1.023	0.099	-10.366	0.035
3C digital parts	-0.287	0.073	-3.929	2.620
Sport wear/sport bags/neck accessories	-0.236	0.112	-2.098	0.510
Interior design	-0.190	0.040	-4.757	0.009
2nd-hand cars	-2.358	0.678	-3.478	0.008
DIY	-0.401	0.187	-2.139	0.116

The intuition for why we find virtually no congestion effect is that for the time period under study, the platform was expanding rapidly, especially on the buyer side. Thus, primary demand dominated secondary demand, with the consequence that sellers were focused on trying to convert new buyers rather than on acquiring existing buyers from other sellers.

Direct Network Effect: Buyer

From a buyer's perspective, Taobao is positioned as a middle to lower end retailer with low prices for a wide assortment of goods. This makes it attractive to a potential buyer. However, given the current business model of the platform, there is no direct economic benefit for a buyer related to the installed base of buyers, i.e., there is no group (buyer) buying, etc. There could be some indirect benefits such as more buyers may signal directly or via word-of-mouth to a new buyer that it is safe to purchase via Taobao. However, given that the escrow system (Alipay) was created for this exact purpose, it seems unlikely that the buyer installed base would be needed as a proxy. A larger installed base of buyers could also induce a wider and more varied assortment of available goods – something that we control for. Overall, our assessment is that, even if there are direct network effects, their magnitude is likely to be second or third-order.

Table 1: Notation

Notation	Definition
B	Buyer
S	Seller
t	time (day)
n_t^B	new registered buyers during time t
n_t^S	new registered sellers during time t
N_t^B	Total number (the installed base) of buyers at the beginning of t
N_t^S	Total number (the installed base) of buyers at the beginning of t
M_t^B	Potential market size for buyers at the beginning of time t
M_t^S	potential market size for sellers at the beginning of time t
U_{it}^B	Buyer's utility of joining the platform
U_{jt}^S	Seller's utility of joining the platform
P_{it}^B	Buyer's probability of joining the platform
P_{it}^S	Seller's probability of joining the platform
z_t^B	The platform's market share of buyers
z_t^S	The platform's market share of sellers
V_t	Product variety index
p_t	Mean transaction price
Q_t^B	Buyer quality
X_t	Seasonality and holiday factors
ξ_t^B	Unobservable buyer factors
ξ_t^S	Unobservable seller factors
ε_{it}^B	Buyer idiosyncratic factor
ε_{jt}^S	Seller idiosyncratic factor

Table 2: Daily New Buyers and New Sellers

	New sellers (1000)				New buyers (1000)			
	mean	sd	Sum	cum sum	mean	sd	Sum	Cum sum
2003*	0.01	0.01	3	3	0.00	0.01	1	1
2004	0.12	0.08	39	42	1.42	1.76	473	473
2005	0.78	0.52	286	328	24.19	12.67	8,831	9,304
2006	2.07	0.51	754	1,082	43.92	6.32	16,031	25,335
2007	2.92	0.73	1,064	2,147	56.82	13.44	20,739	46,075
2008	4.66	1.20	1,707	3,854	115.75	31.20	42,364	88,439
2009	7.68	2.02	2,805	6,659	156.11	47.24	56,981	145,419
2010	10.54	3.43	3,848	10,507	197.30	45.09	72,014	217,434
2011	15.85	4.47	5,785	16,292	236.47	57.65	86,312	303,746
2012	13.86	3.30	5,072	21,364	359.46	91.74	131,562	435,308
All years	6.15	5.96	21,364		125.38	119.49	435,308	

*New sellers start from 5/11/2003, and new buyers from 10/15/2003

Table 3: Summary of Daily Transacting Buyers and Sellers

	transacting sellers / total sellers (%)		transacting sellers/discounted total sellers (%)		transacting buyers/ total buyers (%)		No. of transactions ('000)		No. of transactions per 100 buyers	
	mean	sd	Mean	Sd	mean	sd	mean	sd	mean	sd
2003	0.42	0.31	0.52	0.39	10.47	15.04	0.01	0.01	12.51	18.00
2004	4.99	4.11	6.34	5.09	1.93	0.97	2.07	2.68	2.56	1.29
2005	11.43	1.78	14.85	2.35	0.76	0.20	42.18	29.34	1.27	0.29
2006	8.36	1.58	11.82	1.97	0.62	0.11	201.16	77.18	1.15	0.21
2007	7.09	0.98	12.16	1.74	0.80	0.15	560.65	194.88	1.59	0.33
2008	6.86	0.98	13.33	1.90	0.98	0.16	1,480.11	505.55	2.24	0.45
2009	6.52	1.02	13.55	2.05	1.05	0.19	3,480.62	789.10	3.00	0.62
2010	5.81	0.80	13.35	1.88	1.11	0.20	5,685.80	1,676.95	3.13	0.67
2011	4.79	0.78	11.14	1.76	1.27	0.29	8,860.72	2,549.62	3.44	0.84
2012	4.66	0.74	13.01	2.40	1.42	0.33	13,015.08	4,013.32	3.54	0.92
All	6.63	2.75	12.02	3.68	1.26	2.40	3,674.00	4,682.64	2.61	2.94

Table 4: Summary of Daily Transactions

Year	Mean item price (yuan)		Expenditure per transaction (yuan)		Expenditure per buyer (yuan)		Daily revenues (million yuan)	
	mean	sd	mean	sd	mean	sd	mean	sd
2003	102.54	265.44	110.73	290.90	121.14	307.07	0.00	0.00
2004	160.17	140.90	232.91	129.10	292.33	134.37	0.36	0.50
2005	30.11	10.34	166.91	27.53	279.84	36.79	6.61	4.32
2006	13.69	3.11	144.61	12.17	265.42	23.98	29.38	12.40
2007	11.54	1.66	162.52	10.71	319.48	24.45	91.72	33.82
2008	13.99	1.99	142.52	20.43	319.63	28.81	203.71	51.78
2009	12.23	1.52	117.48	17.94	329.22	31.45	404.68	103.27
2010	12.62	1.46	122.21	16.01	339.07	26.12	684.99	205.94
2011	13.82	1.81	125.00	13.52	335.27	31.40	1,104.46	339.76
2012	14.74	1.64	125.13	16.44	307.40	27.95	1,612.17	512.77
All years	34.7	91.8	145.68	90.65	298.17	104.47	435.54	574.67

Table 5 Main Parameter Estimates

	Buyer model						Seller model					
	OLS		2SLS: separate estimation		2SLS: joint estimation		OLS		2SLS: separate estimation		2SLS: joint estimation	
	est	se	est	se	est	se	est	se	est	se	est	se
Ln(item price)	-0.021	0.017	-0.018	0.017	0.010	0.016	0.076	0.013	0.049	0.050	0.074	0.044
Product variety	1.476	0.070	1.316	0.083	1.241	0.074						
buyer quality							4.958	0.430	5.401	0.497	3.229	0.449
New Year	0.009	0.043	0.005	0.043	0.002	0.039	-0.137	0.033	-0.132	0.033	-0.139	0.029
CNY	-0.309	0.025	-0.322	0.026	-0.332	0.023	-0.644	0.020	-0.637	0.021	-0.660	0.020
Labor day	-0.115	0.035	-0.102	0.035	-0.099	0.031	-0.320	0.026	-0.334	0.029	-0.346	0.027
National Day	-0.115	0.029	-0.124	0.029	-0.125	0.025	-0.356	0.022	-0.366	0.023	-0.382	0.021
Ching Ming	-0.007	0.056	0.005	0.056	0.007	0.045	-0.071	0.042	-0.064	0.042	-0.074	0.035
Dragon Boat	-0.065	0.056	-0.065	0.055	-0.069	0.048	-0.101	0.042	-0.107	0.042	-0.118	0.037
Mid-Autumn	0.087	0.056	0.076	0.056	0.072	0.049	-0.178	0.043	-0.153	0.044	-0.169	0.037
11/11	0.548	0.120	0.552	0.120	0.547	0.109	-0.230	0.092	-0.215	0.093	-0.159	0.078
12/12	0.149	0.120	0.141	0.120	0.134	0.103	-0.133	0.093	-0.110	0.095	-0.011	0.083
Mon	0.069	0.013	0.071	0.013	0.072	0.012	0.087	0.010	0.086	0.011	0.096	0.009
Tue	0.050	0.013	0.052	0.013	0.052	0.012	0.136	0.010	0.137	0.011	0.142	0.010
Wed	0.047	0.013	0.048	0.013	0.049	0.012	0.137	0.010	0.138	0.011	0.144	0.010
Thu	0.037	0.013	0.037	0.013	0.037	0.012	0.135	0.010	0.137	0.011	0.141	0.010
Fri	0.048	0.013	0.050	0.013	0.050	0.012	0.093	0.010	0.093	0.010	0.097	0.009
Sat	0.013	0.014	0.011	0.013	0.011	0.012	0.024	0.010	0.022	0.010	0.020	0.009
CF			-0.033	0.011	-0.038	0.010			0.030	0.015	0.029	0.013
CF^2			0.024	0.004	0.024	0.004			0.007	0.001	0.008	0.001
σ (s.d.)					0.199	0.012					0.151	0.013
ρ (correlation)					0.211	0.027						
N	3,301		3,301		3,301		3,301		3,301		3,301	

CF: control function

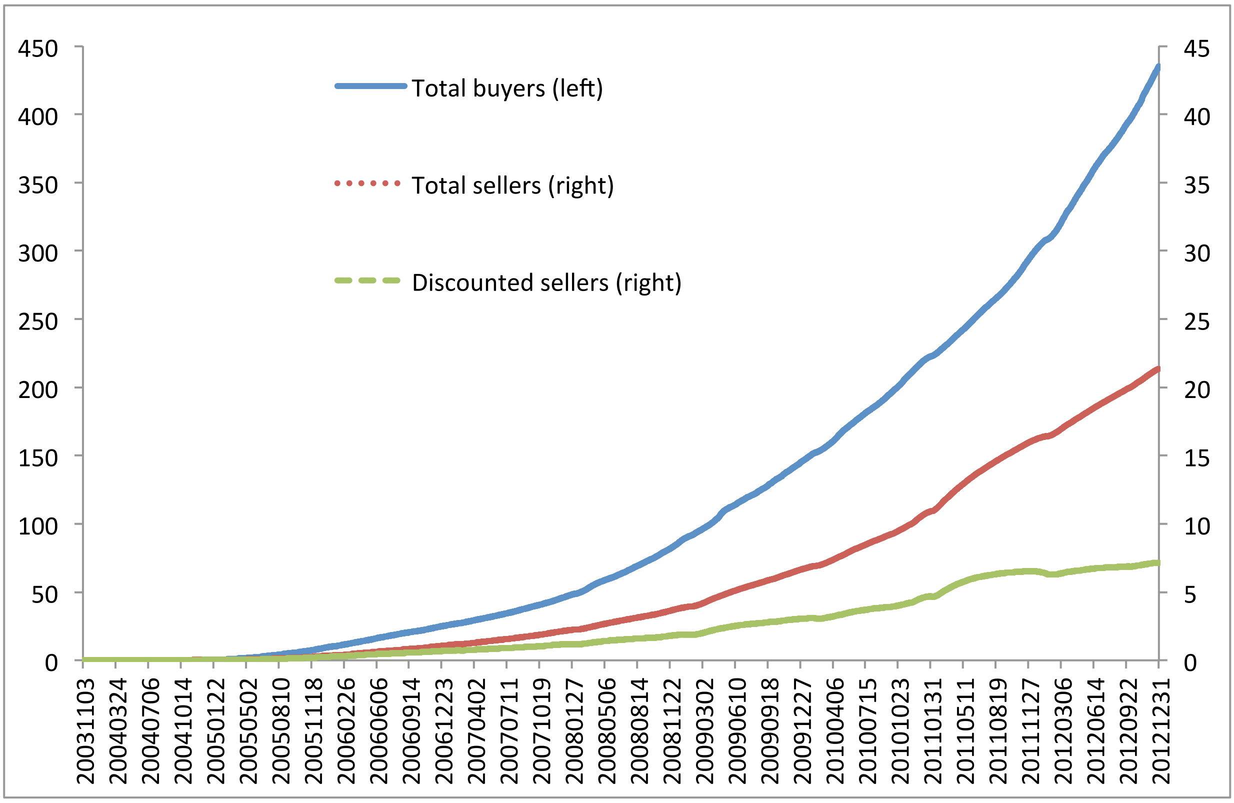

Figure 1: Evolution of Buyer and Seller Installed Bases

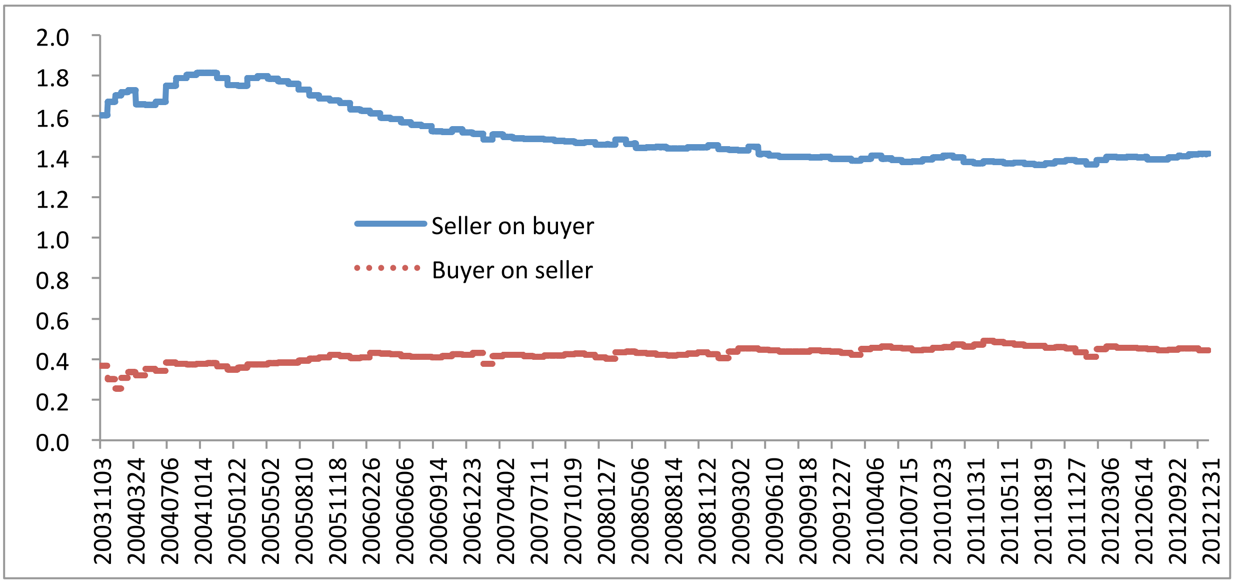

Figure 2a: Evolution of Cross-network Effects (2SLS, joint estimation)

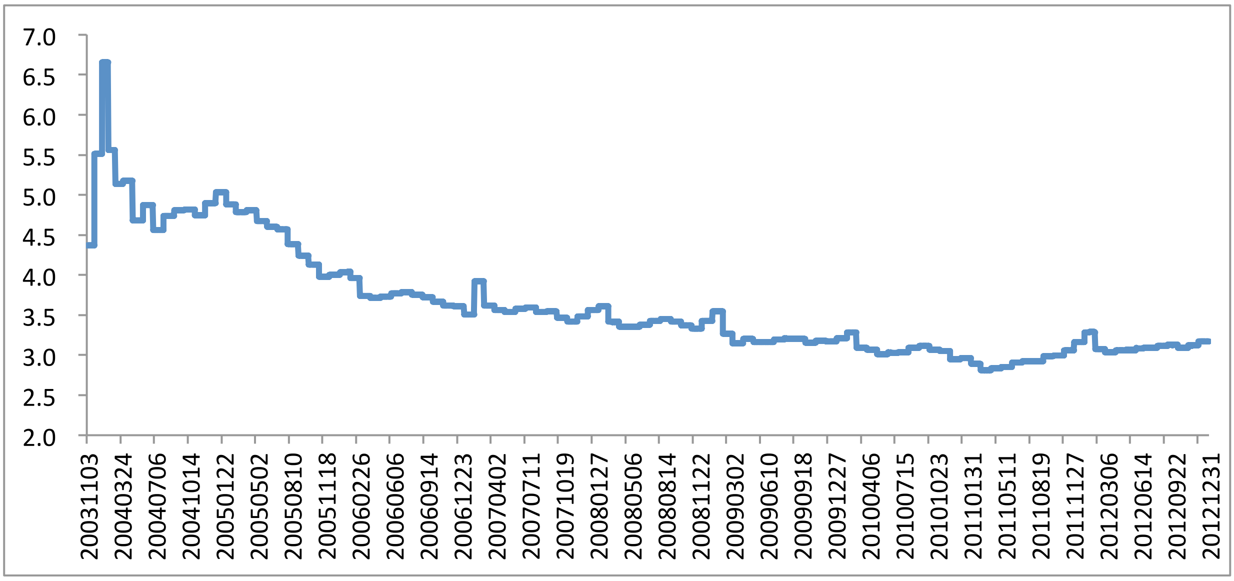

Figure 2b: Ratio of Cross-network Effects: Sellers on Buyers / Buyers on Sellers

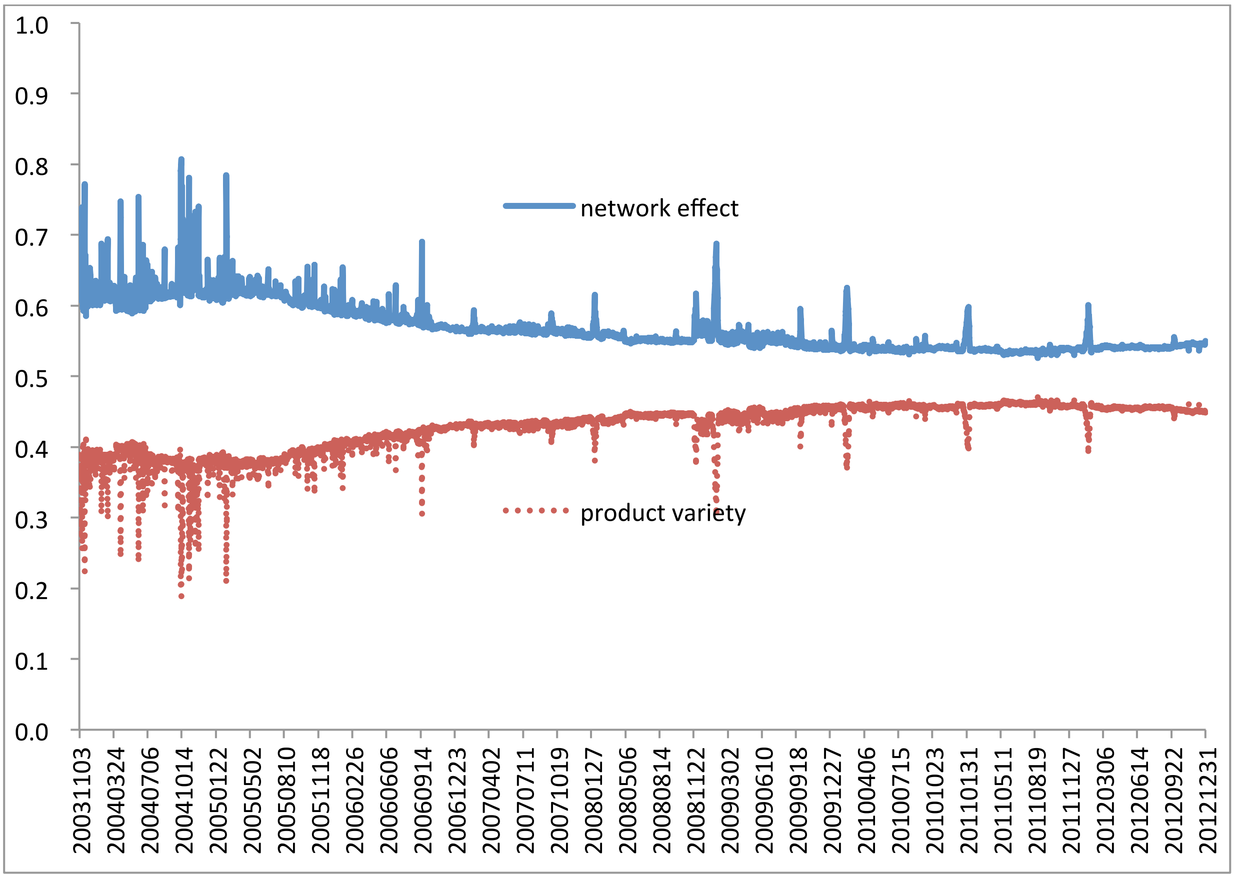

Figure 3a: Relative Contribution to Buyer Growth

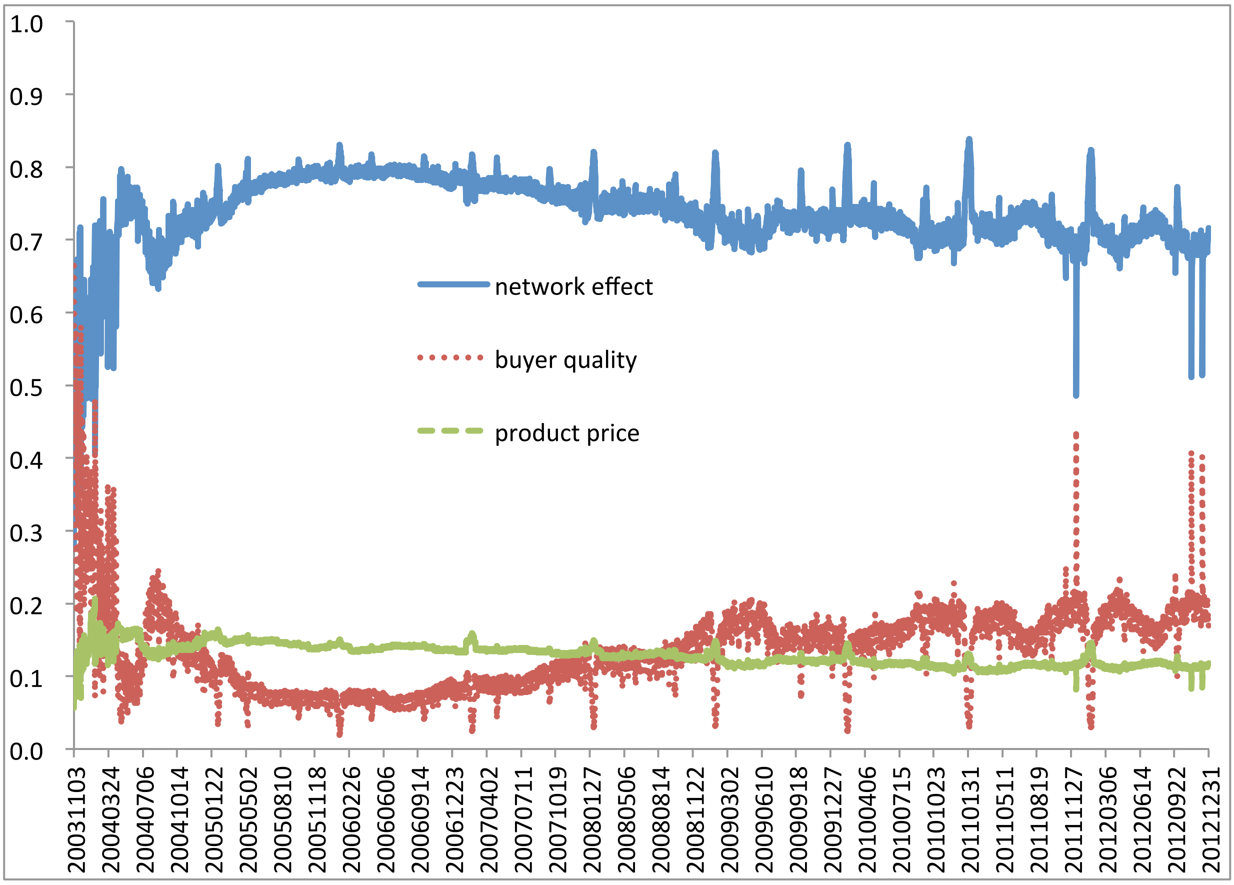

Figure 3b Relative Contribution to Seller Growth

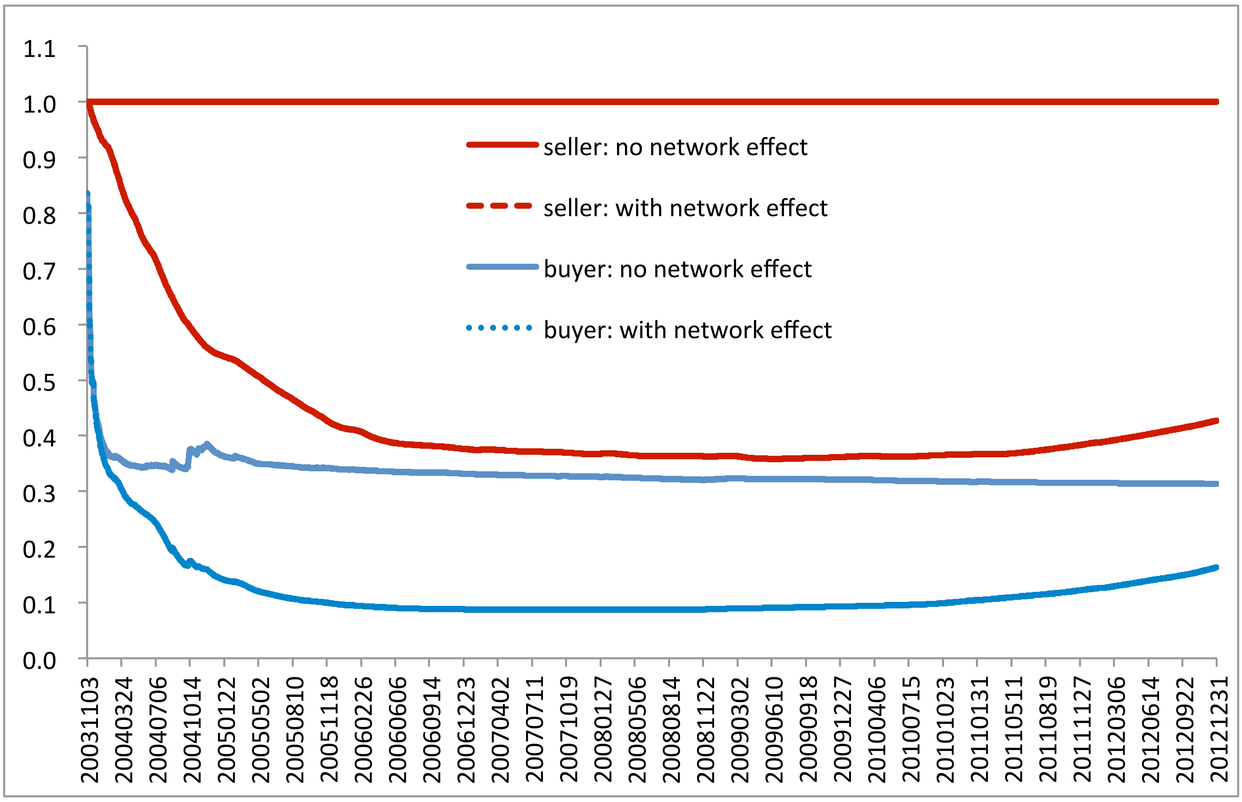

Figure 4: Simulated Impact of Product Variety on Buyer and Seller Installed Bases

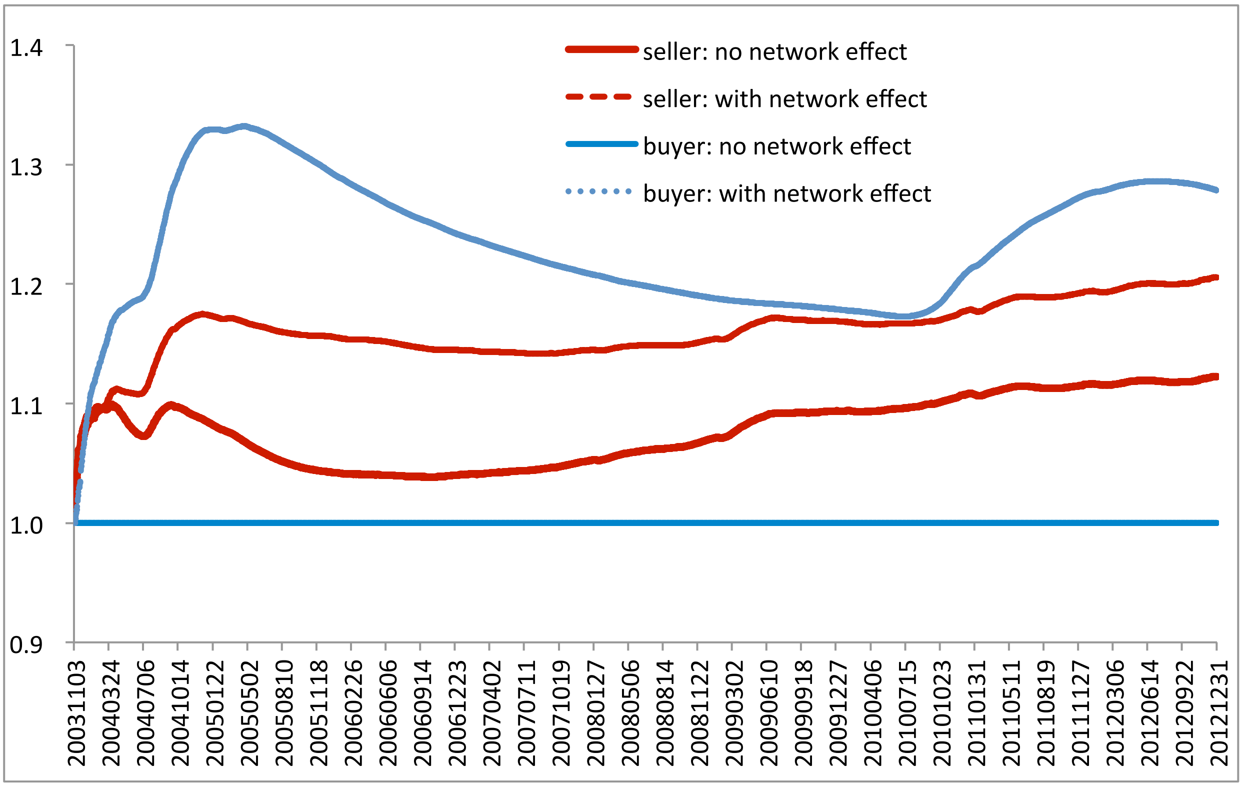

Figure 5: Simulated Impact of Buyer Quality on Buyer and Seller Installed Bases