Paper to be presented at: DRUID17
NYU Stern School of Business, New York, June 12-14, 2017
Platform Dynamism: Sellers' Responses to Design Change and Implications for Platform Effectiveness

Wesley Wu-Yi Koo
Stanford University
Management Science & Engineering
shwesley@stanford.edu

Abstract
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Wesley W. Koo
Doctoral Candidate
Department of Management Science and Engineering
Stanford University
shwesley@stanford.edu

Charles E. Eesley
Assistant Professor, Morgenthaler Faculty Fellow
Department of Management Science and Engineering
Stanford University
cee@stanford.edu
ABSTRACT

How do platform outcomes interrelate with sellers’ strategies? Existing work on the platform-seller relationship can be divided into two streams. The first stream shows that platforms manage seller behavior by changing design features such as ranking algorithms. The second stream shows that sellers are capable of strategizing around existing platform conditions. An important gap remains: we have yet to form a dynamic view of platform evolution – an understanding of how sellers strategically respond to a platform’s design changes and how their strategies in turn affect platform outcomes. Using a seller-level panel dataset from Alibaba’s Taobao.com, we find that after an ambiguous design change, sellers with high social capital tend to correctly interpret the design change and respond with a strategy that is aligned with the platform’s goals. However, sellers with low social capital tend to implement a misaligned strategy. Importantly, this “alignment gap” persisted for months and detracted from the platform’s overall effectiveness. This study primarily contributes to the platform literature by demonstrating the dynamic relationship between sellers and platforms: platform evolution is a result of not only platform action, but also seller reaction.

Keywords: platforms; design change; seller strategy; social capital

INTRODUCTION

A large number of entrepreneurial businesses operate as sellers on multi-sided platforms, which are defined as interfaces that facilitate value-creating exchanges between buyers and sellers (Cennamo & Santalo, 2013; Gawer, 2009). Amazon’s two million third-party merchants have propelled the platform toward record-breaking performance (Reuters, 2017). Sellers on Alibaba’s Taobao and Tmall generated sales that comprised 11.3% of China’s annual consumer retail (China Daily, 2016). Research shows that sellers’ actions are crucial for a platform’s
growth and success (Adner & Kapoor, 2010; Kretschmer & Claussen, 2016). However, as the number of sellers grows, how to effectively guide the behavior of sellers has become a major challenge for platforms (Eisenmann, Parker, & Van Alstyne, 2009).

In response, platforms often create a variety of features to orchestrate seller behavior. These features form an important component of the platform design (i.e., the collection of interface features used by buyers and sellers). By regularly tweaking the platform design, such as when Airbnb rolled out the Price Tips algorithm to guide apartment owners’ pricing decisions, platforms attempt to control the trajectory of platform evolution (Baldwin & Woodard, 2009). Much like government bodies that may create rules that firms must follow, platforms can be conceptualized as “regulators” that set the rules of exchange faced by sellers in the marketplaces (Boudreau & Hagiu, 2009).

There are two streams of research that examine the platform-seller relationship. The first stream focuses on how platforms attempt to shape the motivation and behaviors of sellers (Armstrong, 2006; Boudreau & Lakhani, 2009; Li & Agarwal, 2016; Parker, Alstyne, & Van Alstyne, 2010). For example, some research using formal models shows that platforms can use first-party content to encourage seller participation (Hagiu & Spulber, 2013). Other research shows that platforms can motivate seller innovation by granting access to the platform (Boudreau, 2010) and by adding different types of sellers (Boudreau, 2012). In particular, Boudreau’s two papers provide some of the first empirical evidence showing how platform design affects seller decisions. Overall, this stream suggests that platforms are capable of guiding and even controlling seller behavior using changes in the platform design.

A second stream focuses on how sellers strategize around existing platform conditions to achieve high performance (Li & Agarwal, 2016; Wen & Zhu, 2017; Zhu & Liu, 2016). For
instance, when threatened by a platform’s attempts at expropriation, software vendors can protect themselves through the use of patents and trademarks (Huang, Ceccagnoli, Forman, & Wu, 2013). Similarly, when facing the “big fish, big pond” dilemma, developers can choose to join a gaming platform that better balances between market access and relative standing (Piezunka, Katila, & Eisenhardt, 2017). Overall, this nascent stream of literature shows that sellers are capable of strategically navigating around existing hurdles on a platform.

Although prior research sheds important light on 1) how platforms attempt to control sellers through creating and changing design features and 2) how sellers strategize around existing platform conditions, it remains unclear how sellers actually respond to a changing platform and how those response strategies may influence platform effectiveness, which is defined as the degree to which the platform advances and achieves its goals (e.g. growth, product innovation) (Altman & Tripsas, 2015). Put differently, the literature lacks a dynamic view of platform evolution, whereby sellers’ strategies are not only dictated by platform actions, but also shape platform outcomes.

One reason why sellers’ responses might saliently reshape platform outcomes is because sellers might develop an incorrect interpretation of a design change. As a result of the potential misinterpretation, they might create strategies that run counter to the platform’s design goals. An example involves eBay: when the e-commerce giant changed its “Best Match” algorithm in 2011 without providing clear directions to sellers, some sellers were mistakenly led to believe that auction-type products were favored by the new algorithm (Mathieson, 2011). However, an increase in auction-type listings would actually be in conflict with the platform’s goal of pivoting away from auctions. As illustrated by the eBay example, once a platform implements a design change, sellers’ lack of understanding of a design change might prompt them to develop
responses that are both unanticipated by the platform and carry unpredictable influence on platform outcomes. In this study, we explore in depth this possibility of seller misinterpretation and unanticipated responses. Specifically, in order to understand the platform-seller relationship and more broadly, platform evolution, we pose the following research question: *How do different types of sellers respond to a platform’s design change and how do their response strategies shape platform effectiveness?*

We examine this research question in the context of China’s e-commerce industry. A leading e-commerce platform, Alibaba’s Taobao.com, carried out an ambiguous design change dubbed “Thousand Faces” (TF). The main goal of this change was to encourage sellers to engage in focused selling. However, not all sellers understood TF and many developed strategies that were misaligned with the platform’s goal. We argue that this is because sellers with low social capital, which is defined as one’s interpersonal ties that lead to valuable information and unique knowledge, could not access the information sources that would help elucidate the design change (Adler & Kwon, 2002; Burt, 2000). Instead, those sellers based their interpretation of the design change on more popular and easily accessible information sources, which in the case of TF pointed them toward an incorrect path.

We make use of a seller-level panel dataset provided by the platform. The panel data is supported by detailed interview data and macroeconomic data on individual prefectures. We present two main findings. First, a seller’s level of social capital is associated with better strategic alignment with platform goals and better performance. Sellers with high social capital have a higher tendency to correctly interpret the design change and implement the aligned strategy (i.e. increase one’s main-category richness), while sellers with low social capital tend to misunderstand the design change and do the opposite. Second, the platform did not achieve its
design goal: as a result of sellers’ misinterpretation, there was an overall decrease in main-category richness. Interestingly, the alignment gap persisted for three months after the design change and resulted in a long-term detraction of the platform’s goals.

This study primarily contributes to the platform research and existing knowledge on platform evolution and platform design. By showing how sellers’ heterogeneous responses may affect (and undermine) platform effectiveness, it empirically demonstrates that platform evolution is a dynamic process of strategic interaction between platforms and sellers. The important lesson is that a platform should fully consider the antecedents and impacts of sellers’ responses before making a design change.

Secondarily, this study advances the research on social capital. Scholars have questioned whether information technologies can foster online linkages that might supplant the usefulness of social capital built through offline, physical interactions (Fountain, 1998; Katz & Rice, 2002). This study demonstrates that, in a setting where all business transactions are conducted online, social capital developed through offline propinquity proves to be indispensable for the interpretation of platform events.

THEORY AND BACKGROUND

Our research question considers the interrelationship between platforms and sellers – that is, how sellers respond to a design change and how their responses affect platform effectiveness. To unpack this dynamic relationship, we review two strands of literature that examine the platform-seller relationship. The first stream of literature takes the perspective of the platform and investigates how platforms manage their sellers through design changes and decisions. It shows that platforms reward seller behavior they want to encourage and punish unwanted behavior (Baldwin & Woodard, 2009). Specifically, platforms use discounted pricing to increase
seller participation (Armstrong, 2006; Parker & Van Alstyne, 2005), broaden sellers’ technological access to encourage innovation (Boudreau, 2010), and change its ranking and reputation algorithms to punish seller behavior that leads to buyer dissatisfaction (Hagiu & Jullien, 2011; Nosko & Tadelis, 2015). These studies suggest that platforms are able to shape the behavior of sellers through reward and punishment mechanisms. One implicit assumption in this stream is that the actions of sellers will largely follow a platform’s design goals and will not shape platform outcomes in major ways.

More recently, a second stream of literature has taken the seller’s perspective. In this stream, scholars argue that sellers are capable of making strategic decisions when facing a preexisting set of platform conditions. For instance, Lanzolla and Frankort (2016) show that sellers can use their offline locations as signals of credibility to potential buyers when it is difficult to convey seller quality on a platform. Huang and colleagues (2013) show that sellers develop protection mechanisms, e.g. trademarks and intellectual property, to protect them from the platform’s imitation of their products. Overall, the second stream shows that sellers adopt a wide range of strategic mechanisms to navigate the competitive landscape on the platform.

In summary, extant literature examines the platform-seller relationship from two different perspectives. Taken together, they show that 1) platforms have developed a variety of design mechanisms to control seller behavior, and 2) sellers are capable of devising strategic mechanisms to navigate around existing platform conditions. Although the existing literature sheds important light on platform design and sellers’ strategic decision making, it remains unclear how sellers respond to a changing platform and whether their responses will follow the platform’s expectations. Although platforms try to anticipate “many firms’ many responses to its imposition of rules and regulations” (Boudreau & Hagiu, 2009: p.169) and often succeed in
doing so (Gawer & Henderson, 2007), this is not always the case. In particular, one reason why sellers’ responses might become unpredictable lies in sellers’ potential inability to understand the platform’s actions: it is dubious whether sellers will always comprehend and follow a platform’s goals in a design change. Sellers might find a design change to be highly ambiguous and hence misinterpret a platform’s goals (as illustrated by the eBay example). Therefore, in this study, we strive to form a more dynamic view of platform evolution – a view that takes into account how different types of sellers interpret and respond to a platform’s design changes and how their responses in turn shape platform outcomes.

**Social Capital and Information Access**

What determines a seller’s ability to interpret design changes? Existing literature shows that different levels of experience, resource endowments, and motivation result in strategic variation among sellers (Boudreau & Jeppesen, 2015; Kapoor & Agarwal, 2016; Yin, Davis, & Muzyrya, 2014). In this study, we focus on one important characteristic – seller’s social capital, defined as the interpersonal and inter-firm relationships that provide access to rare and valuable knowledge and information (Adler & Kwon, 2002; Koka & Prescott, 2002).

Social capital theory postulates that the type of information one can access depends on the “social structure within which the actor is located” (Adler & Kwon, 2002: p.18). Being connected to dissimilar social circles yields a “vision advantage” and allows one to be more aware of fast-changing market conditions (Burt, 2005; Rowley, Behrens, & Krackhardt, 2000). Moreover, being in close proximity to individuals with important knowledge and information leads to higher performance and rate of innovation especially in an ambiguous market environment (Laursen, Masciarelli, & Prencipe, 2012; Reagans, 2011). Overall, existing research on social capital suggests that a one’s connections with and physical proximity to important
information contacts will determine their ability to obtain the most accurate platform-related information when such information is not readily available to the public.

In the platform context, two sources of information are of particular importance for the interpretation of design changes – information from experts and information from peer discussion. Platform experts, who are often past platform employees or well-connected individuals with ties to platform rule makers, carry with them inside information that can greatly elucidate the meaning of a design change. The head of an online seller of automatic doors said:

“Oftentimes, many rule changes on the platform are quite subtle and hard to interpret. But there are these platform gurus in Beijing – who are the bosses, chiefs of operation, and traders at other seller firms – who can see through the veil. You must go on a pilgrimage to obtain the scriptures (qujing) from these gurus.”

We argue that sellers with higher level of social capital have a higher chance of reaching and communicating with those experts. This argument is also supported by our interviews. The founder of a successful seller of flowers and vases pointed to the possibility that some urban sellers have privileged access to “inside information” while more rural sellers do not enjoy the same level of access:

“The most successful rural sellers closely observe what successful urban sellers do. For example, this one big store in Guangzhou – it would make a move every time the platform changes something. It probably has some inside information. But for most rural sellers … they just read some ‘surface news’ (biaomian xinwen).”

The second source of information is derived from peer discussion. We argue that sellers with high level of social capital can engage in personal discussions with other sellers to decipher what a design change entails. Simply reading about a design change online does not always paint an accurate picture because the understanding of an ambiguous environmental change requires that relevant information be conveyed in face-to-face conversations (Borgatti & Cross, 2003; Cross & Cummings, 2004). This line of logic is supported by our interviews, as the CEO of an
online books seller pointed to the creation of self-organized learning groups for interpreting platform measures.

“We have organized a tribe (buluo) of 270 sellers. We invite all these brilliant sellers into the tribe, and we discuss selling strategies and platform rules. We take trips together to Qingdao and abroad. For small businesses, without engaging in discussion, it will be the ‘month of the horse, year of the monkey’ \(^1\) before they figure out what the platform changes actually mean!”

In summary, we borrow from existing research on social capital and argue that sellers’ connections to platform experts and peers will enable them to obtain important information related to design changes. Those connections will help sellers better understand a platform’s design goals and align their post-change strategies with those goals. In the next section, we contextualize our theorization within one specific design change that many sellers found to be highly ambiguous.

“Thousand Faces”: An Ambiguous Design Change

The design change of focus is dubbed “Thousand Faces” (TF) and took place in May 2013 on Alibaba’s Taobao.com. Prior to the change, the platform experienced two major issues: 1) poor matching: buyers are looking for one specific type of products, but their search results are dominated by a few average-quality products that do not match their tastes; 2) traffic concentration: a few large sellers and popular products were able to monopolize the vast majority of buyer traffic, leaving most sellers with little traffic (TaoZhiJia, 2015). To address these issues, the platform implemented TF. The official statement conveyed TF to sellers in this way:

“TF will utilize big data from Taobao.com to construct an interest profile for each buyer. It will promote products whose attributes match buyer profiles, displaying those products in buyer’s search results. This will help sellers lock onto potential buyers and implement targeted marketing (jingzhun yingxiao).” (ChinaZ.com, 2013)

\(^1\) Chinese proverb meaning that something will take a prolonged or unpredictable amount of time.
In an interview that was widely reported at the time, a vice president of the platform said:

“We wish our sellers can become more like farmers, who can till their own field for a long time.” (Sina.com.cn, 2013)

These official statements have made the design change highly ambiguous. For sellers, knowing that one should conduct “targeted marketing” and become more like “farmers” does not clarify what the platform was going to reward and punish. Later analysis reveals that the platform essentially aims to encourage *focused selling* – that is, a seller should focus on enriching buyers’ experience within one main product category. This is because not only is each buyer assigned a specific profile based on their past shopping history and demographic information (e.g. “middle-aged woman who likes pantsuits and the color purple”), each seller is also assigned a unique profile (e.g. “a seller specialized in pantsuits who sells primarily to middle-aged women”) (ebrun, 2016). Then, a product is matched with a buyer based on not only the match between the buyers’ search and the product characteristics, but also on the match between the seller’s and the buyer’s profiles. Therefore, a seller can firmly establish its profile by having a diverse set of products within one category that consistently attracts one type of buyer. This is confirmed by a specialized e-commerce consultancy, which conducted a series of A/B tests and found that having an identifiable profile became greatly important for sellers after TF. It argued that a seller should focus on offering a wide range of high-quality products within one category, enhance buyers’ shopping experience within that category, and “stop thinking about ‘catching’ everyone” (Paidai, 2013).

On the other hand, the more popular and less specialized sources of information were often overly simplistic and, worse, led sellers toward incorrect paths. For example, a post on zhihu.com, China’s most popular Q&A community, said that the purpose of TF was mainly to “decentralize” (Zhihu.com, 2013). Another post on Baidu’s Jingyan, a popular knowledge-
sharing website, said TF aimed to “construct an all-encompassing big market” (Baidu Jingyan, 2013). Thus, the most popular information channels actually prompted sellers to reduce product focus in the main category, which was in conflict with the platform’s design goals.

Returning to our theorization on social capital, we argue that sellers’ ability to accurately understand and act upon TF depends on their ability to access the more specialized sources of information (e.g. e-commerce consultants and platform “gurus”). Sellers that are better connected to experts and peers will be more likely to reach those specialized sources as opposed to having to rely on popular sources, which in this case pointed sellers toward the incorrect direction. In the next section, we divide TF into two stages and form hypotheses around sellers’ responses and their effects on platform outcomes.

**Stage 1: After TF – An Alignment Gap.** Immediately after TF, the official sources stated that the design change aims to “promote products whose attributes match buyer profiles” and encourage sellers to “till their own field”. That language is both vague and incomplete, so access to expert and peer knowledge is vitally important for understanding what type of strategies the design change will reward. Due to the variation in sellers’ social capital and access to secondary information sources, we theorize that there will be a considerable amount of heterogeneity in sellers’ strategic responses because different information sources would point sellers toward different directions in the case of TF.

We expect that sellers with more social capital will be more likely to access the more specialized sources of information, which will provide more accurate advice on how to best respond to TF. On the other hand, sellers with less social capital will be unable to engage in the same level of discussion with platform experts and peers and will base their decisions upon the readily available, more popular information sources. Thus, those sellers will be more likely to
adopt the incorrect strategy that is misaligned with the platform’s goals. Overall, the variation in sellers’ social capital will lead to an alignment gap among sellers. Since the new algorithms will be rewarding seller strategies that are better aligned, we also predict the formation of a performance gap as a result of sellers’ varied responses.

**H1. After TF, a seller’s social capital will be associated with an increase in alignment with the platform’s design goals. That is, it will drive a seller’s tendency to enrich its main product category.**

**H2. After TF, a seller’s social capital will be associated an increase in performance.**

How will the patterns of strategic alignment among sellers affect the platform’s effectiveness? In this study, we define platform effectiveness as a platform’s ability to fulfill its design goals. Specifically, since we argued that social capital and rich information access is itself a rare resource that is available to certain well-connected sellers, we expect that most sellers will instead utilize more of the “surface news” – the more popular and simplistic information sources that might prompt sellers to increase their product scope. Therefore, the net effect of the design change will be a higher level of misaligned strategy than aligned strategy. In other words, collectively, the sellers’ responses will detract from the platform’s goal of focused selling. Our theorization leads to the formation of the following hypothesis.

**H3. After TF, the sellers’ responses will have a net-negative impact on platform effectiveness.**

**Stage 2: Over Time - Persisting Misalignment.** Research on diffusion and competitive advantage predicts that as market information diffuses toward the disadvantaged sellers, it will be difficult for initially advantaged sellers to hold on to their competitive advantage (Lieberman, 1987). The diffusion of explicit knowledge and different ways to obtain that knowledge can take place through word of mouth and the relocation of individuals (Aime, Johnson, Ridge, & Hill,
Therefore, through the diffusion of platform-related information, one might expect that the alignment gap among sellers will gradually narrow over time.

However, when it comes to sellers with little social capital, there is reason to believe that the relevant information might not diffuse as quickly as one expects. This is because many of these sellers reside in areas that are distant from the centers of information. Research shows that new technology-related information is inherently slow to diffuse to remote areas due to lack of communication with technological centers (Stern, Adams, & Elsasser, 2009). The slowness to ruminate on external information is also supported by our interviews. As a rural government official in charge of e-commerce oversight said:

“They [rural sellers] lack the awareness (yishi). Months after some rule changes, they don’t even know what happened!”

In summary, although the diffusion of relevant information might help sellers that low in social capital catch up with more advantageous sellers, the former might face adoption barriers even if the information reaches their respective regions. Thus, we expect that their strategies will continue to be comparatively misaligned, and the collective impact of the sellers’ responses will continue to be negative over time. With that, we form the last set of hypotheses.

**H4.** *Over time, a seller’s social capital will continue to be associated with an increase in alignment with the platform’s design goals. That is, it will continue to drive a seller’s tendency to enrich its main category.*

**H5.** *Over time, the sellers’ responses will continue to have a net-negative impact on platform effectiveness.*

**METHODS**

**Data Descriptions**
Taobao.com is a leading e-commerce platform that facilitates C2C online shopping. In 2014, the platform hosted over six million sellers, which were selling to over 200 million active buyers. This setting is particularly appropriate for studying design changes and platform-seller interactions. According to a top-level manager involved in algorithmic design between 2011 and 2015, “small rule changes happen all the time, but major changes take place every five or six months.” The setting may thus yield a window of observation that is of appropriate length for major design changes. Moreover, for TF in particular, we can observe the specific month in which it took place (May, 2013), which allows us to clearly identify time periods before and after the design change.

Our data consists of three parts: panel data on the seller-month level; interviews conducted over a period of three years; and hand-collected microeconomics and development data on Chinese prefectures. A comprehensive panel dataset is particularly well suited for uncovering dynamic relationships and more complicated behavioral patterns (Hsiao, 2007). Given our objective of delineating the dynamic platform-seller interactions on a changing platform, detailed panel data are a necessity.

Moreover, we acquired the panel data directly from the platform; to the best of our knowledge, this is the only panel dataset the platform has provided to external researchers. Specifically, the dataset consists of monthly data on a randomly selected population of 1,838 sellers from March, 2013 to August, 2015. This gives us three months pre-TF and three months post-TF. The sellers are located in 76 prefectures across seven provinces: Shanghai (municipality), Shandong, Jiangsu, Zhejiang, Anhui, Jiangxi, and Fujian. In addition to the panel dataset, we collected macroeconomic and development data on the 76 prefectures from national, provincial, and prefecture-level yearbooks. These data are used as important control variables.
and the instrumental variable. Finally, we support our theorization and findings with interview data collected over 280 hours of field research in six Chinese provinces. The interviews were conducted in eight interview trips from 2013 to 2017, four of which were carried out by one of the authors and the other four by local assistants. Our interview subjects consist of sellers (rural and urban), platform staff (low-, medium-, and high-level managers), and government officials.

**Measures**

**Dependent Variables.** Let $i$ represent the $i$-th seller, and $t$ the $t$-th month in the panel. The dependent variable for H1 and H4 is the monthly *Main-Category (MC) Richness*$_{it}$.

This variable indicates the degree of alignment with the platform’s goal of encouraging focused selling – that is, for sellers to enrich its portfolio in the main product category. A sellers’ main category is defined as the category with the highest amount of sales. From detailed analysis of TF presented earlier, we know that a category’s richness consists of two aspects – diversity of products and buyer experience (the degree of satisfaction from browsing and purchasing from a seller’s product line). MC Richness is thus measured in the following manner:

$$MC \text{ Richness}_{it} = \log (n_{it,MC} \times dsc_{it}/5)$$

(Eq. 1),

where $n_{it,MC}$ is the number of distinct products listed by seller $i$ in its main category in month $t$, and $dsc_{it}$ is the average review score buyers gave to seller $i$ in month $t$ for the seller’s product descriptions (out of 5). We argue that $n$ is a measure for product diversity and $dsc$ is a measure for buyers’ collective experience from browsing a seller’s product portfolio.

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2 Per agreement with the platform, the dataset only contains information on the three highest-grossing categories.

3 A distinct product must have its unique webpage, unique product name, and unique combination of underlying keywords.
The dependent variable for H2 is logged $Sales_{it}$.

Lastly, the dependent variables for H3 and H5 are the platform-wide Average MC Richness, which take the average of MC Richness for all sellers in a given month.

**Independent Variables.** The first independent variable is the design change shock, $Post-TF_i$. Since the design change took place in mid-May, 2013, we treat the months of March, April, and May as pre-change ($Post-TF_i = 0$). For Stage 1 – After TF (Hypotheses 1-3), we treat the month June as post-change ($Post-TF_i = 1$). For Stage 2 – Over Time (Hypotheses 4 and 5), we treat the months of June, July, and August as post-change.

The second independent variable is Social Capital, which is proxied by the degree of urbanness in a seller’s registered location. Rural sellers’ ties are mostly based on kinship and neighborhood solidarities, which lowers the amount of nonredundant information that can be passed through (Beggs, Haines, & Hurlbert, 1996; Burt, 1992). Being located in a rural area also impedes the formation of unique ties and the flow of important market information, especially when the information needs to be interpreted through personal conversations (Wiggins & Proctor, 2001). Overall, research shows that being located in a rural area is associated with significant lower level of social capital – interpersonal ties that lead to valuable business information and knowledge. In the context of TF, as shown by the interview evidence, we see a comparative lack of social capital on the part of the rural sellers.

From the data, a seller’s location is divided into six levels ranging from the village to the city center: the village (cun), the township (xiang/zhen), the county (xian), the rural outskirts of a city (shijiao), the city proper (shinei), and the city center (shizhongxin). Every prefecture (e.g. Hangzhou, Suzhou) contains all six levels; the difference is that a large prefecture like Hangzhou

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4 All sales data are multiplied by one unknown number to ensure anonymity; similarly for all price data.
will have a large city center and city proper, whereas a smaller prefecture will have a small city center and a large rural area. We then construct a discrete variable the value of which ranges from 1 to 6, with 1 representing villages (low on social capital) and 6 representing first-tier cities (high on social capital). Lastly, Social Capital$_i$ is then multiplied with Post-TF$_i$ to yield an interaction term in order to test Hypotheses 1, 2, and 4. Figure 2 shows a histogram of the sellers organized by different levels of social capital. Only 3% of the randomly drawn sample consists of county-level sellers; we verified this piece of information with the platform and received the answer that indeed very few sellers are registered at the county-level.

**Control Variables.** We also include a group of owner-level, seller-level, and region-level control variables. First, it is imperative to control for the attributes of a seller store’s individual owner. To do that, we control for the owner/CEO’s Gender$_i$ (dummy variable, female = 1) and Age$_i$. These attributes may drive a seller’s performance and strategic decision-making. Owner’s age is included as a discrete variable, with 1 to 6 corresponding to under 18, 18 to 22, 23 to 29, 29 to 35, 36 to 50, and over 50 years of age, respectively.

The second set of control variables control for seller-level attributes. They include seller’s Firm Age$_{it}$, monthly average buyer Review Score$_{it}$, and monthly average Price$_{it}$. Firm age is measured as number of months since seller founding. Review score is the average of three review scores – reviews for a seller’s product description, service, and logistics (maximum score = 5). We take the natural log of the average price of all distinct products in the top three product categories to calculate the Price variable.

Third, we construct a set of location-specific variables to control for the level of economic and technological development in a seller’s local prefecture: annual per capita GDP$_i$, (10,000 RMB’s), Education Level$_i$, Internet Penetration$_i$, and Road Infrastructure$_i$. All location-
specific data are collected from local, provincial, and national yearbooks. Data for GDP, education level, and roads are from 2013, and data for Internet penetration is from 2011, the most recent years for which data is available for all prefectures. Education Level is measured as the percentage of a prefecture’s population that is enrolled in high schools. A relatively high level of education in a region may lead a seller to develop better business models and better interpret a design change. Internet penetration is measured as the percentage of a prefecture’s population that has access to the Internet. A region with high Internet penetration may indicate greater familiarity and deftness with information technology, which may affect their performance and strategic decision-making. Road infrastructure is a density measure calculated by dividing the total length of highway in kilometers by the area of a prefecture in squared kilometers. Better road infrastructure in a region enables a seller to better deliver their products and more easily interact with sellers in other places, which point to improved performance and better access to information that needs be communicated face-to-face.

Lastly, we include dummy variables product Category and Time Trends (month dummies). The inclusion of product category controls is crucial: it controls for time-invariant heterogeneity associated with different types of products, as one concern is that there might be systematic differences in product categories across different levels of social capital.

Analysis

In an ideal world, we would want to randomly assign different levels of social capital (measured as the degree of location urbanness) to sellers and observe the impact on sellers’ strategic responses and post-TF performance. In our empirical setting, we need to model the random assignment of social capital using observational data. In the process, we have to address
potential omitted variable and selection biases. As a preview, we will rely on a range of analytical methods that include an instrumental variable approach and matching sub-samples.

To test Hypotheses 1, 2, and 4, we compare how different types of sellers strategize before and after the design change. Specifically, we adopt panel linear models with random effects. Random effects models allow the use of time-invariant variables as predictors and are appropriate when we aim to draw inferences about the entire seller population. The following equation represents the main model of choice:

\[
MC \text{ Richness}_{it} = \beta_0 + \text{Information Access}_i \beta_1 + \text{PostTF}_i \beta_2 + \\
\text{PostTF}_i \times \text{Information Access}_i \beta_3 + C_{it} \lambda + D_i \delta + \text{Time Trends}_t \tau + \alpha_i + u_{it}
\]

(Eq. 3),

where \(C_{it}\) represents the time-variant control variables, \(D_i\) represents the time-invariant control variables, \(\alpha_i\) is the seller-specific unobserved heterogeneity, and \(u_{it}\) is the error term. Although the Hausman test rejects the null hypothesis and suggests the use of fixed effects models, it is less valid in the context of panel data, especially when time-invariant variables are valuable to interpretation (Baltagi, 2013). To mitigate the concerns associated with model choice, all relationships are tested using fixed effects models as additional analysis. In our models, we choose not to include a lagged dependent variable on the right hand side because doing so creates a downward bias on the coefficients of other variables, even though it may dramatically improve the regression fit (Achen, 2000).

To test Hypotheses 3 and 5, we employ a repeated-measures ANOVA method to compare the average MC Richness on the platform before and after TF. This method is particularly appropriate for measuring changes in a related sample over time, where a simple t-test does not qualify due to the latter’s assumption of sample independence (Howell, 2012).
RESULTS

Table 1 reports the summary statistics and the matrix of pairwise correlation. To recap, this is a sample of 1,838 sellers over a period of six months. Table 1 shows that 50.5% of the sellers have female owners, and the average owner age is around 29 years old (level 4 in the age variable). The average seller has been in business for 16.1 months. Among the control variables, one concern is that GDP per capita and Internet Penetration are highly correlated, as both point to the level of development in a particular region. To assuage the multicollinearity concern, we separately dropped each variable in additional regressions and calculated the variance inflation factors (all below 3). It is important to note that multicollinearity issues associated with control variables should neither affect the coefficient estimates on the independent variables nor reduce the collective predictive power of the controls.

Insert Table 1 about here

In Hypotheses 1 and 2, we predict that shortly after TF, sellers with higher social capital will tend to devise the appropriate strategy that is more aligned with platform goals (i.e. increase main-category richness) and achieve higher performance. We first show graphically the platform change effects on different types of sellers. In Figure 3, we graphed the average main-category richness of high-social capital (city proper, city center, and city outskirt) versus low-social capital sellers (county, township, and village) in the sample for a period of four months. As shown in the figure, the richness of both groups of sellers is relatively in sync prior to the design change in period 5. After the design change, however, there was a noticeable divergence in their strategic choices. This provides graphical evidence supporting Hypothesis 1. In Figure 4, we illustrate the difference in the strategic choices of the two groups of sellers by mapping out the
percentage change in average main category richness across the seven provinces. For high-social capital sellers, the majority of the provinces show no change or mild increases in richness after TF. For low-social capital sellers, most provinces show sizeable decreases in richness. In Figure 5, temporal patterns in average sales provide initial support for Hypothesis 2: although low-social capital sellers on average outperformed high-social capital sellers prior to the design change, the latter’s sales performance took off and took over shortly after period 5.

Table 2 displays the regression results for Hypotheses 1 and 2. Some noteworthy results on the control variables emerge. Higher buyer reviews lead to more product richness but less sales, which indicates the presence of high-quality, low-volume sellers. A seller store’s length of operation (Seller Age) drives both richness and sales, which speaks to the importance of e-commerce experience. Owner’s Gender is not related to richness or sales, which is in contrary to prior work that generally finds a performance discount associated with female entrepreneurs. Lastly, the results show that the coefficient estimates remain stable when controls for product categories are absent.

Table 2, Model 2 supports Hypothesis 1: the positive coefficient (p < 0.05) on the Post-TF × Social Capital interaction term indicates that, after the design change, high-social capital sellers tend to have significantly higher main-category richness than low-social capital sellers. In terms of effect size, one level higher in the social capital spectrum (e.g. from city outskirt to city proper) translates to about 3.0% more product richness after the design change. Table 2, Model 4 supports Hypothesis 2: the positive interaction effect (p < 0.1) indicates that, after the design change, high-social capital sellers significantly outperform low-social capital sellers. One
additional level in the social capital spectrum translates to 3.3% higher sales after TF. Overall, results for the first two hypotheses strongly support the statement that, shortly after the design change, higher social capital and better information access enables sellers to devise the correct strategy that aligns with platform goals.

---

Insert Table 2 about here

---

Next, we examine the overall change in the average seller richness on the platform after TF. As shown in Table 3, in the month after TF, the average seller’s main-category richness actually decreased by 4.6% compared to the pre-TF trend. A repeated-measures ANOVA suggests that the change is mildly significant at the 0.11 level. Regardless of the significance level, we can be confident that collectively sellers on the platform did not become more focused after TF. Therefore, this result strongly supports Hypothesis 3, which predicts that the overall effect of the design change would be one of detraction from the design goal of focused selling.

Lastly, we move to test Hypotheses 4 and 5, which make the same predictions as in Hypotheses 1 and 3 for an extended period of time after TF. In Figure 6, we show the trajectory of product richness for an additional three months after TF. Although low-social capital sellers gradually increased their richness, a gap opened up and did not seem to narrow over time. In fact, by the end of period 8, the average high-social capital seller (at the city center, city proper, and city outskirt levels) has a portfolio that is 16% richer than the average low-social capital seller (at the village, township, and county levels).

---

Insert Figure 6 about here

---
Table 4 strongly supports Hypothesis 4, which predicts that the alignment gap due to variation in social capital will persist over time. Models 2 and 3 show that being one level higher in the social capital spectrum on average generates about 2.8% greater richness in a seller’s main category. This effect is not significantly different from the 3.0% in the testing of Hypothesis 1 (shortly after TF). Therefore, this result indicates that social capital continues to be an important factor in shaping a seller’s strategic decision-making three months after the design change took place. Meanwhile, Table 5 supports Hypothesis 5, which predicts that the negative effect of the sellers’ responses on the platform’s overall effectiveness (defined as the platform’s ability to advance its goal of encouraging focused selling) will persist over time. Through a second repeated-measures ANOVA, we find that there is the average main-category richness on the platform did not increase since the first month after TF. In other words, the platform failed to induce its sellers to focus on and enrich their main product categories long after the design change.

Robustness Checks

Instrumental Variable Analysis. The main model would be able to obtain a consistent estimate of location effects if sellers’ social capital is exogenously determined. However, it could be a conscious choice on the part of the owner to be somewhere yields better social capital and richer information, and that choice could be influenced by entrepreneurial quality and strategic thought. As a result of the endogeneity issue, the social capital variable could be correlated with the errors terms, which would make the coefficient estimates inconsistent. To address this issue, we adopt an instrumental variable approach to generate exogenous variation in the social capital.
variable (Cameron & Trivedi, 2005: 4.8). Specifically, we instrument a seller’s social capital with the Return Migration pattern in a seller’s prefecture. We argue that high level of return migration to an area with less social capital (more rural location) leads to a higher tendency for an owner to start their store in that area. However, the exclusion restriction is satisfied because return migration should not have a direct impact on a seller’s strategic response to the design change. An F test does not indicate a weak-instrument problem. Migration is measured as the average annual percentage change in rural labor force over the period 2008-2012, adjusted for natural population growth. Table 6 presents the results from instrumental variable analysis. The rate of return migration is a strong predictor for a seller being located in a low-social capital area (Table 6, Model 1, First Stage). We then used the fitted values from the first stage to form the instrumented values of the social capital variable, Instrumented Social Capital. Shown in Table 6, Models 2 and 3, the interaction term Post-TF × Instrumented Social Capital is significantly and positively related to change in main-category richness and sales performance. Moreover, the coefficients are similar in effect size to those in the main models. Therefore, the instrumental variable analysis mitigates some of the key endogeneity concerns and provides greater confidence in our findings.

Unambiguous Change. To further tease out the importance of social capital, we need to test our proposed relationship in the context of a clearly defined, unambiguous design change. Therefore, we managed to obtain additional data from the platform for the time period around October 2014, which corresponds to a clear-cut design change related to sellers’ pricing level. The issue prior to the change was that there were too many low-priced items on the platform and
it caused a decrease in buyer experience and overall product quality. To address this issue, the platform announced in September that on October 10, it would allow buyers to evaluate low-price products, which were protected from buyer reviews prior to the design change because low-priced products would generally receive overwhelmingly poor reviews (Taobao, 2014). The message was clearly delivered and the design goal was easy to gauge by most sellers – to discourage sellers from competing over price. Regressions not shown here compare pre- and post-change price levels and show that there is a significant increase in the prices listed by most sellers after the design change, and a seller’s social capital is not related to its tendency to increase their prices. In other words, in the case of a relatively unambiguous design change, most sellers devised the aligned strategic responses regardless of their levels of social capital.

**Additional Analyses.** We implemented additional analyses that are not reported in the paper. First, we adopted alternative measures for the degree of focused selling. Specifically, we measured the degree of selling focus by using a seller’s product dispersion across the categories and by calculating the relative ranking of its main-category richness among all sellers in the focal seller’s main category. Our results remain stable for all alternative measures.

Second, to further address the concern that sellers might be systematically different across the social capital spectrum, we conducted two matched sub-sample analyses. Specifically, we matched sellers based on their MC Richness prior to TF and on their tendency to change their portfolios prior to TF. The two sub-samples are about one quarter of the main sample in sample size. However, our regressions show that the results remain stable for these sub-samples and the coefficient estimates are similar to those in the main models.

Moreover, one may question whether the random effects model or the fixed effects model should be used to test our proposed relationships. Although our use of the random effects in the
main models is a conscious decision to utilize more of the time-invariant data (Baltagi, 2013), we also ran all models using fixed effects instead of random effects. Results remain similar across the board.

Lastly, one concern related to the mechanism is that it could be differences in the endowment of physical and financial resources that prevented low-social capital sellers from making the necessary attempts at alignment. First, we emphasize that sales volumes before the design change were on average similar across the social capital spectrum, which suggests that the different groups were similarly endowed in terms of financial resource accumulation. Second, we ran regressions on two sub-samples consisting of sellers that were founded before May 2012 (one year before the design change) and those founded after May 2012. The rationale is that younger sellers are generally less endowed with the financial and physical resources that enable successful adaptation (e.g. Kimberly, 1976). In the context of e-commerce, most sellers are small businesses and it is exceedingly rare for new sellers to obtain substantial initial capital; only through the accumulation of sales over time do some sellers to become more endowed. Therefore, young sellers should be generally resource-constrained and there should be less variation in resource richness in the younger sample than in the older sample. However, regressions show that the effects of social capital on post-change performance and strategy are similarly positive for both young and old sellers, which indicates that sellers’ social capital drives performance and strategic alignment in spite of differences in the endowment of physical and financial resources.

**DISCUSSION & CONCLUSION**

Using a panel dataset directly acquired from a major e-commerce platform, this study contains two main findings. First, after an ambiguous design change aiming to encourage more
focused selling among sellers (i.e. increase in main-category richness), a seller’s social capital became a strong driver of one’s ability to align with platform goals and improve their performance. Second, the pattern of misalignment was persistent for at least three months after the design change, and the varied seller responses resulted in a decrease in the overall level of focused selling. As a result, the design change did not fully accomplish its starting goals and the platform witnessed an overall decrease in effectiveness. This study contains major implications for the emerging research on platform evolution and design. Secondarily, this study also advances our understanding of offline social capital in an online business environment.

Implications for Platform Research

This study makes a major contribution to the emerging platform research (Baldwin & Woodard, 2009; Boudreau, 2012; Cennamo & Santalo, 2013; Zhu & Liu, 2016). The contribution is two-fold. First, by investigating the antecedents and consequences of seller strategy, this study is among the first to examine the interrelationship between platforms and sellers and highlight the dynamism in platform evolution (Boudreau & Jeppesen, 2015). It empirically demonstrates a feedback loop in which a design change is followed by heterogeneous seller responses, which in turn affect platform effectiveness. In so doing, this study responds to a call in research to explore the dynamic “platform-complementor interactions” that affect a platform’s growth trajectory (McIntyre & Srinivasan, 2017: p.156).

Second, despite the importance of sellers in driving network effects and encouraging innovation (e.g. Clements & Ohashi, 2005; Li & Agarwal, 2016), very little work has investigated how sellers strategize in light of platform control (Kapoor & Agarwal, 2016). This study empirically demonstrates that heterogeneity among sellers leads to highly varied performance and strategic patterns after a design change. For sellers, it is important to know the
amount of influence (and power) they have over platforms. For platforms, it is important to analyze the characteristics of different types of sellers, who may respond unexpectedly to the same design attempt. Intelligent management of sellers can spark innovation and growth, but unexpected reactions from sellers may also hurt platform growth (Boudreau & Jeppesen, 2015; Li & Agarwal, 2016). Gaining knowledge of sellers’ response patterns will thus help platforms better predict seller behavior and control the trajectory of platform growth.

**Implications for Social Capital**

Scholars have long questioned whether the increased sharing of information online will supplant the role of offline, interpersonal social capital in producing valuable knowledge (Fountain, 1998; Wellman, Haase, Witte, & Hampton, 2001). One argument is that in an increasingly digitized business world where all transactions and rule changes take place online, the locus of business activity should shift from offline networks to online interactions. This study offers some of the first empirical evidence for the usefulness of offline social capital on a fully digitized market environment. The main insight is that even though there exists ample amount of platform-related information online, businesses often encounter difficulties in their interpretation and analysis of the market conditions, the elucidation of which will require personal communication with social contacts.

This study is limited along several dimensions, which open up exciting avenues for future research. First, it focuses on one specific design change. Although TF is broadly representative of other platform changes in the sense that it aims to advance platform goals through orchestrating seller behavior, future research may examine different design changes on other types of platforms (e.g. service-oriented platforms such as Uber). Second, this study is conducted
within the boundary of one platform. Future work can empirically examine competitive (and cooperative) processes that take place between platforms after one platform carries out a design change. A couple of interesting questions to ask are: how does one platform respond to changes on another platform, and how do multi-homing sellers shape the design strategies of different platforms?

In conclusion, this study explores how platform outcomes interrelate with seller strategy. We argue that sellers’ heterogeneous strategic decisions can advance or detract from a platform’s goals depending on seller-specific attributes such as social capital. Our findings paint a highly dynamic picture of platform evolution: the development of a platform is a result of not only platform action, but also seller reaction.

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Strategic Management Journal.


FIGURES & TABLES

FIGURE 1
Description of the Proposed Relationships
FIGURE 2
Distribution of Sellers By Degree of Social Capital (Village = Low Social Capital; City Center = High Social Capital).

FIGURE 3
MC Richness of High-Social Capital Versus Low-Social Capital Sellers After TF.
FIGURE 4
Mapping of Average Percentage Change in MC Richness among High-Social Capital Versus Low-Social Capital Sellers.

High Social Capital:

Low-Social Capital:

FIGURE 5
Sales of High-Social Capital Versus Low-Social Capital After TF.
FIGURE 6
### TABLE 1
Descriptive Statistics and Matrix of Correlation

<table>
<thead>
<tr>
<th>Variable</th>
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<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
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<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
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</tr>
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<td>7.499</td>
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TABLE 2
Effects of Social Capital on MC Richness (H1) and Seller Sales (H2) After TF.

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<th>Model 3</th>
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<td>MC Richness</td>
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<td>log(Sales)</td>
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<td>4,405</td>
<td>4,405</td>
<td>4,405</td>
<td>4,405</td>
</tr>
<tr>
<td>Adjusted R2</td>
<td>0.021</td>
<td>0.022</td>
<td>0.207</td>
<td>0.208</td>
</tr>
</tbody>
</table>

Panel linear models with random effects estimates. Two tailed tests. *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

TABLE 3
Change in Average Sellers’ MC Richness After TF (H3).

<table>
<thead>
<tr>
<th></th>
<th>Before TF</th>
<th>1 month after TF</th>
<th>ANOVA (repeated measures)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average MC Richness</td>
<td>1.481</td>
<td>1.433</td>
<td>Shows decrease in sellers’ MC Richness</td>
<td>0.11+</td>
</tr>
</tbody>
</table>
TABLE 4
Effects of Social Capital on MC Richness Over Time (H4).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MC Richness</td>
<td>MC Richness</td>
<td>MC Richness</td>
</tr>
<tr>
<td>log(Price)</td>
<td>-0.072*** (0.014)</td>
<td>-0.075*** (0.014)</td>
<td>-0.065*** (0.015)</td>
</tr>
<tr>
<td>Review Score</td>
<td>0.114*** (0.034)</td>
<td>0.109*** (0.034)</td>
<td>0.124*** (0.034)</td>
</tr>
<tr>
<td>Owner Gender</td>
<td>0.033 (0.031)</td>
<td>0.035 (0.031)</td>
<td>0.030 (0.032)</td>
</tr>
<tr>
<td>Owner Age</td>
<td>0.023 (0.015)</td>
<td>0.024 (0.015)</td>
<td>0.001 (0.015)</td>
</tr>
<tr>
<td>GDP p.c.</td>
<td>0.009 (0.009)</td>
<td>0.008 (0.009)</td>
<td>0.000 (0.009)</td>
</tr>
<tr>
<td>Internet Penetration</td>
<td>-0.249 (0.398)</td>
<td>-0.316 (0.400)</td>
<td>-0.074 (0.403)</td>
</tr>
<tr>
<td>Road Infrastructure</td>
<td>-0.031 (0.041)</td>
<td>-0.040 (0.041)</td>
<td>-0.026 (0.041)</td>
</tr>
<tr>
<td>Education</td>
<td>2.154 (2.818)</td>
<td>2.364 (2.814)</td>
<td>3.094 (2.835)</td>
</tr>
<tr>
<td>Seller Age</td>
<td>0.004*** (0.001)</td>
<td>0.005*** (0.001)</td>
<td>0.002* (0.001)</td>
</tr>
<tr>
<td>Post-TF</td>
<td>-0.176*** (0.039)</td>
<td>-0.163*** (0.046)</td>
<td></td>
</tr>
<tr>
<td>Social Capital</td>
<td>0.000 (0.010)</td>
<td>0.000 (0.010)</td>
<td></td>
</tr>
<tr>
<td>Social Capital × Post-TF</td>
<td>0.028*** (0.010)</td>
<td>0.028*** (0.010)</td>
<td></td>
</tr>
<tr>
<td>Category Dummies</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Time Dummies</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>0.664*** (0.239)</td>
<td>0.744*** (0.240)</td>
<td>0.570** (0.269)</td>
</tr>
</tbody>
</table>

Observations: 6,808
Adjusted R2: 0.0001

Panel linear models with random effects estimates. Two tailed tests. *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

TABLE 5
Change in Average Sellers’ MC Richness Over Time (H5).

<table>
<thead>
<tr>
<th></th>
<th>Before TF</th>
<th>1 month after TF</th>
<th>3 months after TF</th>
<th>ANOVA (repeated measures)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average MC Richness</td>
<td>1.481</td>
<td>1.433</td>
<td>1.431</td>
<td>Shows decrease in sellers’ MC Richness</td>
<td>0.019**</td>
</tr>
</tbody>
</table>

Shows decrease in sellers’ MC Richness
## TABLE 6
Instrumental Variable Analysis.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1 First Stage</th>
<th>Model 2 Second Stage (After TF)</th>
<th>Model 3 Second Stage (Over Time)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Social Capital</td>
<td>MC Richness</td>
<td>MC Richness</td>
</tr>
<tr>
<td>Return Migration</td>
<td>-0.203***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.030)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Instrumented Social Capital x Post-TF</td>
<td>0.036**</td>
<td>0.032***</td>
<td></td>
</tr>
<tr>
<td>(0.015)</td>
<td>(0.010)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4,405</td>
<td>4,405</td>
<td>6,808</td>
</tr>
<tr>
<td>Adjusted R2</td>
<td>0.134</td>
<td>0.022</td>
<td>0.018</td>
</tr>
</tbody>
</table>

Panel linear models with random effects estimates. Two tailed tests. *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.