Marketplace Expansion through Marquee Seller Adoption: Externalities and Quality Implications*

Wenchang Zhang  
Kelley School of Business · Indiana University  
wenzhan@iu.edu

Wedad Elmaghraby, Ashish Kabra  
Robert H. Smith School of Business · University of Maryland  
welmaghr@umd.edu, akabra@umd.edu

In the race to establish themselves, many early-stage marketplaces choose to accelerate their growth by adding marquee (established brand name) sellers. We study the implications of marquee seller adoption on smaller, lesser-known unbranded sellers in the marketplace. While recent literature has shown that higher-quality unbranded sellers fare better than their lower-quality peers, we posit that this tendency may depend on the quality of entering marquee sellers. To this end, we collaborate with a B2B platform and exploit its two marquee sellers’ adoptions of contrasting qualities. Using a difference-in-differences framework, we causally identify the effect. We find that while higher-quality unbranded seller revenues increase relative to low-quality unbranded sellers when the entering marquee seller is of high quality (consistent with the literature), the effect is reversed when the entering marquee seller is of low quality. Further, unbranded sellers change their supply quantities such that their average supply quality shifts in the direction of marquee entrant quality. Using a stylized theoretical model, we identify two mechanisms that drive our findings – (i) new buyers brought in as a result of the marquee’s entry disproportionately favoring unbranded sellers of neighboring quality, and (ii) the unbranded seller’s ability to adjust their supply quantities. Our findings have implications on marquee sellers’ adoption strategies for marketplaces where sellers strategically set their supply quantity (a key feature of several marketplaces, including many gig-economy marketplaces). The choice of marquee sellers, examined through the lens of their externality on unbranded sellers, can foster or undermine the platform’s long-term growth objectives.

Key words: marketplaces, empirical OM, quantity competition, difference-in-differences.

*We gratefully acknowledge support from our data sponsor. We thank Martin Bichler, Tian Chan, Oguz Cetin, Vivek Choudhary, Anand Gopal, Will Ma, Jorge Mejia, Saša Pekeć, Danko Turcic, and Gabriel Weintraub for comments and discussions. Seminar participants at Boston College, Cornell, Empirical OM Workshop (Wharton), IU Kelley, Nanyang Technological University, Stanford GSB, UC Riverside, University of Illinois at Chicago, and INFORMS Workshop on Market Design provided valuable feedback.
1. Introduction

In 2007, the idea of Airbnb was born when its founders rented out three airbeds in their San Francisco apartment. Today, Airbnb boasts millions of rental listings, varying in quality and prices – a far cry from the initial offering portfolio. While the ability to grow and expand offerings is imperative for many businesses to succeed, it is much more so for such online platforms where it can be particularly challenging to keep and grow the buyer base due to expanding options and low search costs. Online platforms offer the opportunity of ease-of-connection and positive network externalities to both buyers/users and sellers; the larger the offerings, the higher the value to potential buyers/users. Growth for these platforms is therefore not only key to more growth, but also to profitability as well as to long-term survival.

While growth on one side of the market can drive growth on the other side and a positive cycle of growth can emerge, it is oftentimes challenging to initiate a positive cycle of growth (small remains small; Caillaud and Jullien (2003)). One catalyst for growth that falls under the category of “growth hacking” is for the platform to attract and onboard marquee sellers. Marquee sellers are typically sellers who have a prestigious brand value and can bring recognizable supply to the platform. Their presence on the platform and associated name recognition attracts new buyers, and oftentimes succeeds in kick-starting a positive cycle of growth. For example, one year after the release of Xbox (a gaming console), Microsoft acquired Bungie, a well-known game developer. Microsoft made this acquisition so it could make Bungie’s popular game Halo available on Xbox, which was done in an effort to expedite the expansion of Xbox’s user base (Edelman 2015). Another example is Huff Post, a leading media platform, who launched its business by hiring well-recognized writers to create high-quality blog posts to attract readers (Choudary 2016).

Although Microsoft’s Bungie acquisition and other similar examples succeeded, not all marquee-seller growth strategies have been as fortunate. For example, eBay invited marquee sellers to its platform during its early years. Marquee sellers’ voluminous new listings discouraged smaller unbranded sellers to participate, resulting in a deceleration of eBay’s expansion in following years (Hagiu and Rothman 2016). Similarly, Amazon Marketplace invited large sellers from China to list their products on its site. Unfortunately, some of these sellers sold lower-quality (often counterfeit) products. As a result of the entry of the low-quality sellers, the supply from high-quality sellers eventually plummeted, and the marketplace’s overall supply quality worsened (Shepard 2017). These failed examples highlight an often-overlooked element in the cycle of growth strategy based on marquee seller entry. It is critical for the platform to consider how the quality of a marquee seller and its entry into the platform will impact existing sellers and the overall ecosystem of the platform.
Extant literature stemming primarily from economics has extensively studied firm entry and market responses. Two common takeaways from the literature are that incumbent revenues suffer in the face of new entry due to intensified competition, and that higher-quality incumbents (those who offer either a higher-quality product and/or a higher-quality service experience) fare better than their low-quality counterparts (Tirole 1988). However, the effect of firm entry in platforms is more nuanced. While intensified seller competition does occur, the positive externalities arising from demand-side creation (whereby the entrant brings in additional buyers) provides a counteracting force. The net result of these two forces on incumbent sellers is unclear. Empirical literature on firm entry in online platforms is rather nascent. Few recent studies (Cao et al. 2019) conclude that incumbents might be better off as a result of increased competition. Moreover, the quality of the incumbents matters. For example, Reshef (2020) finds that high-quality incumbents fare better than low-quality incumbents when competition increases.

Building on the literature, we ask: How does quality of the entrant influence the performance of existing sellers? While a higher-quality (existing) seller has the advantage of quality when competing with its low-quality peers for demand (a competitive dynamic that is independent of the entrant’s quality), the quality of an entrant can have a differential effect on the ‘new’ demand an existing seller experiences. The classic competition lens portends higher demand competition for sellers closer in quality to the entrant. This negative impact of entry for existing sellers must be considered against possible (associated) demand growth. In online platforms, entrants can bring new buyers/users to the marketplace. More specifically, high-quality entrants may attract new buyers who are quality-conscious, while low-quality entrants are likely to bring in new buyers who are less quality-conscious (more cost-conscious). Taken together, the implications for existing sellers’ net demand would therefore likely depend on the entrant’s quality and is not easily determined a priori.

In addition to the demand-side dynamics brought about by the entry of a marquee seller, it is necessary to study the accompanying supply-side dynamics so as to accurately capture the net impact of entrant quality on existing sellers. A key feature of contemporary online platforms that informs this investigation is supply flexibility; sellers may be able to alter their supply quantities more easily than their brick and mortar counterparts. Supply flexibility is particularly important in competitive environments where sellers are often price takers. It is plausible that existing sellers’ supply responses will differ based on their own quality as well as the quality of the incoming marquee seller. This in turn has implications for the portfolio of supply-quality offerings on the platform.

In this paper, we examine both the supply-side and demand-side dynamics induced by a marquee seller’s entry. To this end, we empirically infer the effect of marquee seller entry and devise a
stylized model to identify the mechanisms behind the overall effect. Our empirical and theoretical settings embody the price-taking supply response behavior of sellers. We are thus also able to shed light on the supply responses of individual sellers and the change in overall supply quality.

To execute our empirical study, we partner with a leading online B2B platform where retailers liquidate their excess/returned inventory. Online marketplaces routinely operate public marketplaces alongside several distinct private marketplaces. In public marketplaces, unbranded sellers list products. Private marketplaces are “online stores” operated individually for branded sellers. For example, Amazon.com operates several private marketplaces alongside its large scale public marketplace.\(^1\) Having a healthy public marketplace is often of strategic importance for many of these online platforms. Managers at CaaStle\(^2\), an online clothing-rental platform with a public marketplace and several private marketplaces, claim that a public marketplace confers many benefits, including allowing retailers who are considering launching a private marketplace to test out the platform by first participating in the public marketplace. In addition, the public marketplace allows CaaStle to have greater visibility into buyer and seller behaviors and to obtain greater detailed and timely information regarding market dynamics and trends.

Akin to these platforms, our partner platform operates a public marketplace (PU marketplace henceforth) where unbranded sellers (typically small- and medium-sized retailers) list their products. In addition, the platform operates several distinct private marketplaces (PR marketplace henceforth) for individual well-known marquee retailers (e.g., Walmart, The Home Depot). The platform features several categories such as Appliances, Consumer Electronics, and Apparel, oftentimes with individual marketplaces offering a variety of categories on their sites. All wares are sold via (proxy) ascending English auctions.

Given the wide range of products sold and their varied paths to arrive at the platform (e.g., some products are brand new yet unsold excess inventory, others are product returns, etc.), buyers rely on sellers’ product descriptions to assess the value of the products. While the platform supports a fairly standardized template for all auctions hosted on its site, individual sellers vary in the degree of information they provide. Furthermore, some sellers’ descriptions of listed products differ significantly from their actual states. Such discrepancies often result in buyers submitting disputes to the platform and seeking financial compensation from the seller and from the platform. While in PR marketplaces, the branded seller’s reputation provides a signal of trustworthiness of their listing information (and hence the likelihood that a dispute will arise), the anonymity of the PU marketplace poses an added layer of challenge for creating efficient markets. In an effort to bring

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\(^1\) For instance, here is Amazon.com’s Dyson store:

\(^2\) https://www.caastle.com/index.html
greater transparency and to improve efficiency of the PU marketplace, the platform tracks these disputes and posts for each seller a historical dispute rate (akin to ratings on other platforms). This measure serves as a useful measure of a PU seller’s trustworthiness and, hence, of a PU seller’s quality for our analyses.

We exploit the first two major (single category focused) marquee entry events on the platform to investigate our specific research questions discussed below. Examining single category entry events allows us to identify treatment and control categories to causally estimate our effects. A key aspect of these two marquee entrants is their differing reputation/quality. While the first entrant is a very high-quality seller (with observed disputes close to zero), the second marquee entrant suffers from a far higher dispute rate than the typical PU marketplace seller (i.e., the second marquee entrant is a very low-quality seller). We refer to the first entrant as a superior entrant (SPR henceforth) and the second as an inferior entrant (IPR henceforth). These entries were staggered over 4 years (presumably providing sufficient time for the PU marketplace to react and adjust to a new norm of platform dynamics). We use a differences-in-differences method for causal identification of the marquee entry effect.

In this context, we answer the following two research questions:

1. Are high-quality and low-quality PU marketplace seller revenues differentially affected by the entry of a marquee seller, and, if so, does the direction of this difference vary with regard to the marquee entrant’s quality?

2. Do PU marketplace sellers’ strategic supply responses vary based on their quality (high-quality versus low-quality), and, if so, does the relative magnitude of these effects change with regard to the marquee entrant’s quality?

With regard to our first research question, the existing literature has found that high-quality incumbent seller revenues increase relative to that of low-quality incumbent sellers after a marquee seller entry (Zervas et al. 2017, Reshef 2020). We find that this is only true if the entrant is of superior quality. When the entrant is of inferior quality, we find that low-quality seller revenues are relatively better. Since the sellers only interact with and affect each other through competition for buyers, examining buyer behavior sheds light on the drivers of the above findings. We find that the PU marketplace sellers lose some of their business to the marquee entrants. However, the buyers who previously shopped with high-quality PU marketplace sellers are lost at a higher proportion than those who shopped with low-quality PU marketplace sellers when the SPR joins, whereas the opposite is true when the IPR joins. We term this as a localized market-stealing effect. Although some extant demand is lost to the entrants, PU marketplace sellers are able to attract new marquee-generated buyers. We find that high-quality PU marketplace sellers attract a higher proportion of these new buyers compared to low-quality PU marketplace sellers when the SPR
joins, and that the opposite is true when the IPR joins. We term this as a localized market expansion effect.

Turning to our second research question, we shed light on sellers’ strategic responses with regard to supply quantities. We find that while high-quality PU sellers expand their supply share relative to low-quality PU sellers when the SPR joins, the low-quality PU sellers disproportionately expand their supply when the IPR joins. This results in the typical quality of PU marketplace listings shifting in the direction of the quality of the entrant. It is interesting to note that, despite high-quality PU sellers enjoying a quality-advantage, the low-quality PU sellers still manage to expand their market presence after the IPR entry.

In addition, we use a stylized theory model to help us better understand the mechanisms of our empirical findings and to assess their boundaries. Our theory model allows us to highlight the key drivers behind asymmetric PU marketplace outcomes based on entrant type – (i) quality-sensitive (quality-insensitive) buyers brought in by high-quality (low-quality) entrants, and (ii) the PU seller’s ability to adjust their supply quantities. Devoid of these features, the effect of entry are consistent with extant norms of thought. Absent (i), the PU sellers of higher quality would fare similarly or better than lower-quality ones upon any marquee entry, and absent (ii), PU sellers’ revenues for those neighboring in quality to marquee entrants would be relatively worse off.

A key implication of our findings is the direction of the externality of a marquee entrant on a PU marketplace’s quality. If platform managers pursuing marketplace expansion fail to incorporate this indirect effect, an unanticipated shift towards one end of the quality spectrum might ensue in the PU marketplace. Thus, a platform seeking to maintain a high-quality PU marketplace reputation may restrict itself to high quality entrants only. On the other hand, a platform seeking to increase overall PU marketplace revenues should also take into account the potential of any entrant to bring along with it a large buyer pool, ideally which is also quality-sensitive. Thus, a platform will need to consider the impact of the new entrant on the PU marketplace quality along with its ability to bring new demand to the marketplace, with the caveat that these two considerations may result in differing entrant recommendations.

This paper makes the following three novel contributions to the literature on online platforms. First, to the best of our knowledge, this is the first paper to examine the externality of the quality of marquee seller entrants on public marketplace sellers’ revenues. We find that results from previous studies do not generalize to entrants of different qualities. Second, we study supply competition within public marketplace sellers, which allows us to understand how public marketplace quality is affected due to entry. This is quite important to highlight given the quantity competition nature (accompanied by price-taking behavior) of unbranded sellers on many current gig-economy platforms. Third, our theoretical analysis sheds light on the mechanisms driving the empirical
findings and allows us to draw boundaries on market settings where the observed empirical findings would hold.

The rest of the paper is organized as follows. §2 summarizes the related literature, §3 describes this study’s empirical setup and dataset, §4 presents the empirical analysis, and §5 discusses the mechanisms of our findings using a stylized model. We discuss the managerial implications and conclude the paper in §6.

2. Literature Review

Our work relates to two streams of literature in the fields of Operations Management, Economics, and related areas. The first stream studies the effects of a competitor entry in an online marketplace, and the second stream focuses on seller supply behavior in online marketplaces.

Past studies on effects of competitor entry in online marketplaces have found that higher-quality sellers fare better than their lower-quality peers. For example, Zervas et al. (2017), which looks at the effect of Airbnb’s entry into the short-term accommodation market find that lower-quality hotels fare worse than high-quality ones. In a food delivery context, Reshef (2020) shows that in terms of revenues, high-quality restaurants are better off than low-quality restaurants when an online platform adds several sellers from an acquisition. However, we find that none of these studies or other existing studies, to our knowledge, examine if quality of the entrant plays a role on its effect on existing sellers. This is the key contribution of our paper.

Relatedly, when faced with a competitor entry, an important lever of strategic reaction in contemporary online marketplaces is changing one’s supply quantity. Studies have looked at these decisions in response to platform actions. For instance, in ride-hailing platforms, Allon et al. (2018), Chen et al. (2021), and Hall et al. (2021) look at the effect of incentives or fares on drivers’ active hours, Cullen and Farronato (2020) finds that sellers’ supply is highly elastic in prices in online platforms, Karacaoglu et al. (2018) examine drivers’ supply location decisions in response to increased competition, Musalem et al. (2019) study how flexibility in supply relates to agent retention and wait times in service platforms, while Kesavan et al. (2014) study how flexible supply affects sales, profits and expenses. We build on and add to this literature by showing that the supply reactions of high- and low-quality sellers differ under marquee entry and also depend on the entrant quality. This lens leads us to novel insights regarding the overall shift in the quality of existing seller listings.

A key driver of our results is the positive spillover due to the network effects on buyers from higher competition. Several studies document how network effects in online platforms can lead to positive effects due to higher competition. Looking at online food delivery, Reshef (2020) discovers positive spillover demand for incumbents due to increased sellers on the platform. In an online B2B
Auction market, Bimpikis et al. (2020) identify that increases in supply-side thickness that results from concentrating listings on specific days of the week effectively and substantially boosts buyers’ participation rates, ultimately leading to positive spillovers. Cao et al. (2019) examine the effect on an incumbent platform from the entry of a new bike-sharing platform and find that the incumbent’s revenue per trip and bike utilization rate benefit from the entry. Adding to this literature, we find that a seller entry not only leads to new buyers joining the platform (the positive network effect), but the quality of the entrant also drives the quality-sensitivity of new buyers who join because of the entrant. This, in turn, determines how the existing sellers of a certain quality are affected. We find that this nuanced notion of network effects is understudied in the literature, and this paper aims to contribute to the literature.

In sum, our study contributes to the literature in three important ways. First, we study the effect of entrant quality. Typically, the empirical literature on this topic has focused on the entry of a single quality competitor. Our context and data allow us to study the impact of entering competitors of varying qualities. Second, we study the supply reactions and resulting shift in quality of an existing marketplace. This adds to the revenue effects that have been studied, in the context of marketplace expansion, in previous research. Third, we identify a nuanced network effect - the quality-sensitivity of entering buyers - which is also a function of the quality of the entrant seller.

Although our work is carried out in the context of an online platform, it is related to entry effects that have been seen in the in brick-and-mortar retailing literature. Brick-and-mortar retailers often choose to co-locate, suggesting positive benefits due to competition (Fujita and Thisse 1996, Ellison et al. 2010, Murry and Zhou 2020). On the other hand, many studies have found that incumbent retailers are significantly negatively affected by the entry of big-box retailers (Gielens et al. 2008, Ailawadi et al. 2010, Haltiwanger et al. 2010). However, not all incumbents are equally affected. Incumbents that are neighboring in distance, industry, format, or assortment are negatively affected, while those that are farther away may be better off (Vitorino 2012, Daunfeldt et al. 2019). As a complement to these studies, our findings highlight that incumbents who are neighboring to the entrant can be better off in online platforms.

In addition, our work also relates and contributes to the burgeoning empirical work in operations management in the contexts of B2B marketplaces (Dhanorkar et al. 2020, Alhauli et al. 2020), ride-hailing (Cohen et al. 2021, Yu et al. 2020), food delivery (Glaeser et al. 2020), and shared lodging (Cui et al. 2020) platforms, among others. Methodologically, we are close to studies such as (Cui et al. 2020, Jiang et al. 2021), who combine empirical and theoretical methodologies to study problems in operations management.
3. Background and Data
Our partner platform is a leading online B2B platform where retailers liquidate their excess/returned inventory using a proxy English auction mechanism. Our data is granular, and we observe all transactions and participants. The platform operates a single public (PU) marketplace, and several private (PR) marketplaces within the same ecosystem. Within the single PU marketplace on the platform, small- and medium-sized unbranded sellers list their products. These sellers’ listings are anonymous (i.e., the buyer cannot determine the identity of the seller), with only the observable dispute rates providing seller reputation and quality signals to potential buyers. The PU marketplace spans several product categories. Some prominent categories are Consumer Electronics, Appliances, Jewelry, and Toys, which account for 49% of platform listings and 71% of total sales. Each PR marketplace hosts the wares of a single branded seller, such as Walmart, with the marketplace carrying the name of the seller.

3.1. Sellers
Each seller belongs to a single marketplace where they list their products. Noticeably, each auction listing typically contains a number of items in the same category (e.g., multiple units of iPhone 7 devices) and of the same conditions (e.g., new, used, or salvaged). Listings typically specify product names, quantities, and conditions. Sellers are required to go through a registration process with the platform when they sign up. Once a seller is registered, creating listings is seamless and requires no intervention from the platform. Each listing typically remains open for 3 days, at which time the item is either awarded to the highest bidder or is taken off of the site if no bids had been submitted. About 89% of listed auctions are sold (i.e., receive at least one bid above their starting price).

**Seller (Informational) Quality:** Buyers rely on sellers’ product descriptions to assess the value of a listings. However, not all descriptions are accurate, with some sellers displaying a higher rate of discrepancy in the described vs. actual state of the products listed. Buyers who have won a listing and find such a discrepancy often notify the platform and seek its assistance as they pursue financial compensation from the seller. Table 1 lists the sources of disputes and their relative frequency for the Consumer Electronics category of the PU marketplace; we note that 70% of the disputes arise due to inaccuracies in the product description (i.e., not as described, item shortage, item damage). To bring greater transparency and improved efficiency to the PU marketplace, the platform tracks and displays each (anonymous) seller’s dispute rate within each auction that a PU seller lists. The dispute rate captures the fraction of a seller’s listings in which the buyer disputes the transaction. This rate measures the trustworthiness of a seller, hence, we use the seller’s dispute rate as a
<table>
<thead>
<tr>
<th>Dispute reason</th>
<th>Percentage (%)</th>
<th>Related to product description?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not as described</td>
<td>51</td>
<td>Yes</td>
</tr>
<tr>
<td>Shipping problem</td>
<td>21</td>
<td>No</td>
</tr>
<tr>
<td>Item shortage</td>
<td>12</td>
<td>Yes</td>
</tr>
<tr>
<td>Other</td>
<td>12</td>
<td>Unknown</td>
</tr>
<tr>
<td>Product not available</td>
<td>2</td>
<td>Yes</td>
</tr>
<tr>
<td>Item damage</td>
<td>2</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Table 1. Dispute reasons in the PU marketplace

measure of the seller’s quality. We denote a PU seller as high-quality (low-quality) if their dispute rate is below (above) the median value (i.e., 16%).

It is important to note that the dispute rate of sellers within a category is not correlated with the type (cell phone, printers, etc.) or the condition of the products (new, used, salvaged) listed by the sellers (Appendix B.2 provides supporting analysis for the Consumer Electronics category). Further, sellers typically do not specialize in one specific product quality (condition) of the products they list. Indeed, only 4% of the sellers list products in a single condition (Appendix B.3 provides supporting analysis). Thus, sellers in our setting are separable along the informational quality dimension but not product quality.

Figure 1 (left panel) displays the frequency and diversity of seller’s quality (dispute rate) in the PU marketplace. These numbers highlight that disputes are not uncommon and that sellers’ qualities vary widely across the marketplace. Furthermore, buyers are sensitive to this quality information and adjust their willingness to pay accordingly. The right panel of the figure depicts the relationship between seller quality and auction final price for used iPhone 6 phone listings of the year 2016 make. We focus on this subset of data to compare products that are similar but for seller quality. The negative correlation suggests that (some) buyers do respond to the quality information and adjust their prices, i.e., are quality sensitive. We also note that an individual buyer’s experience with a seller is limited (a buyer bids on an average of 6 auctions throughout their lifetime or 0.5 auctions per week). Thus, a seller’s dispute rate should be an important factor in guiding a buyer’s choice of a seller.

We also note that, in our data, an individual PU seller’s quality (dispute rate) does not change significantly over time (i.e., high-quality (low-quality) PU sellers remain high-quality (low-quality) over time). This stability in dispute rates is reasonable in our setting given that seller item descriptions are a function of their upstream supply processes. Some sellers have tight control and visibility over the products they source and are therefore able to describe their listings accurately and maintain low dispute rates, while others source from aggregators and re-sellers who do not pass along accurate information. This, in turn, leads to auction listings that are not described accurately and in high dispute rates for these sellers. While sellers could plausibly adjust their quality (a
Figure 1. PU seller dispute rates (for all PU sellers) (left). Buyers’ quality-price relationship in purchasing used iPhone 6 of 2016 make (right).

Note: 1. The slope of the fitted regression line is negative at 0.05 significance level. 2. The quality-price relationship is presented only for iPhone 6 of 2016 year listings so that the effect of sellers quality on final prices of similar products is illustrated.

A similar dispute rate resolution and tracking mechanism exists for PR marketplace sellers, although the platform does not display dispute rates publicly on each listing. Despite the absence of this information on the platform, buyers often leave reviews of PR sellers on social media platforms (e.g., YouTube) and review platforms (e.g., trustpilot.com) and can learn about the quality of an entrant through these channels.

Entrant Types. We focus our analysis around the first two major single category marquee entry events on the platform. A key aspect of these two entry events is their differing quality. The first entry event involves two large, branded retailers whose marketplaces on the platform launched in January of 2013 and March of 2013. Given the almost simultaneous timing of their entries, the fact that both of these entrants (marketplaces) were of high-quality with (emergent) near zero dispute rates, and that both marketplaces sold products in only the Consumer Electronics category, we consider them a single entry for our analysis. We refer to this entry event as the creation of a superior PR marketplace (SPR) seller. The second entry is of a large, branded retailer who launched its PR marketplace in July of 2015 and, similarly, only sold products in the Consumer

In Appendix B.1, we formally show that marquee entry has no statistically significant effect on individual PU sellers’ quality using a difference-in-differences method.
Electronics category. During its first year of launch, this marquee entrant had an unusually high dispute rate of 39%, which is a particularly poor quality level when compared to unbranded sellers in the PU marketplace. Therefore, we refer to this entrant as an *inferior* PR marketplace (IPR) seller.

Prior to our focal entry events, a handful of PR marketplaces were created. However, each of these earlier entrants sold products across numerous major categories present on the platform. This multi-category presence prevents us from identifying a reasonable control group (a key component in our analysis). Hence, our study is conducted on the first entrants who sold in a single category (consumer electronics).

### 3.2. Buyers

The buyers on the platform are typically small re-sellers. In a typical week, about 33% of active\(^4\) buyers place a bid. Over the course of a week, buyers who bid, on average, bid on 3 auctions, win 0.8 auctions, and purchase $1,935 worth of merchandise. Buyers are free to participate in any of the marketplaces in which they are registered (PU or PR marketplaces).\(^5\)

We label buyers based on the marketplace in which they first register; PU (PR) marketplace buyers are those whose first registration is on the PU (PR) marketplace. Further subdividing, SPR (IPR) buyers are buyers whose first registration is on the SPR (IPR) marketplace. In Table 2, we report buyer and marketplace level summary statistics. During the time period surrounding an SPR’s entry, PU buyers bid in 3.65 PU (2.19 pre-entry and 2.61 post-entry) and 1.33 SPR listings, while SPR buyers bid in 1.99 PU and 11.28 SPR listings. Similarly, post IPR’s entry, PU buyers bid in 11.17 PU (5.80 pre-entry and 8.82 post-entry), and 1.59 IPR listings, while IPR buyers bid in 5.64 PU and 15.77 IPR listings. These statistics imply that (i) bidders bid at a disproportionately higher rate in the marketplace in which they first registered, and (ii) bidders do cross-bid (participate) across marketplaces. This would suggest that bidders do actively search for products across markets and participate in those aligned with their price and quality preferences.

### 4. Empirical Analysis

We proceed by analyzing the effect of marquee entry on the revenues and supply levels of PU marketplace sellers. We first describe our identification strategy, which we then execute in the rest of the section.

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\(^4\) We assume that buyers are active between the first and the last times they bid.

\(^5\) Registration requires an application along with a valid business license.
### Table 2. Buyers’ summary statistics in Consumer Electronics category.

<table>
<thead>
<tr>
<th>Buyer type</th>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Buyers</td>
<td>814</td>
<td>2,251</td>
</tr>
<tr>
<td></td>
<td>227</td>
<td>345</td>
</tr>
</tbody>
</table>

In PU listings:

- Avg. participated auctions: Superior Entry = 3.65, Inferior Entry = 11.17, 5.64
- Avg. purchased auctions: Superior Entry = 1.01, Inferior Entry = 2.86, 1.36

In PR listings (post-entry period only):

- Avg. participated auctions: Superior Entry = 1.33, Inferior Entry = 11.28, 15.77
- Avg. purchased auctions: Superior Entry = 0.19, Inferior Entry = 2.48, 2.37

Note: 1. Cross-bidding-related descriptive statistics are in bold. 2. The numbers in the braces show the averages for pre-entry and post-entry periods separately. 3. The sum of pre-entry and post-entry split is higher than average per buyer because of entry-exit of buyers resulting in averaging over different set of buyers for the two calculations.

### 4.1. Identification Strategy

We posit that the timing of the marquee entrants’ arrival to the platform is exogenous, which allows us to treat their entries as natural shocks. Although decisions with regard to which marquee entrant, and hence which categories, to add to the platform are strategic actions taken by the platform and can be endogenously determined, the exact timing of entry is exogenous as far as the PU sellers and all buyers on the platform are concerned. Addition of marquee sellers to the platform is a contractual process that involves discussion and negotiations between the platform and the marquee seller. Once the legal and contractual negotiations are finalized, it can take several weeks before a new PR marketplace goes live online. During this time, the platform does not make any pre-announcements (e.g., “coming soon”) to notify existing PU sellers or buyers of the impending entrant’s arrival. In addition, the entries do not appear to be driven by any upstream economy-level shocks, as the growth in revenues in the entrant categories (Consumer Electronics, Smartphones) in the United States were stable around the time periods included in the analysis (see Figure 7 in Appendix C).

Despite the exogeneity of marquee entry, a before-after analysis of the impact of entry may still not be an appropriate and unbiased form of analysis due to significant time trends, as well as (unobservable to us) platform-level changes (e.g., website upgrades) around the timing of marquee entries. If unaccounted for, these may introduce significant bias into our estimates. To address this, we use, from the same platform, a control group that shares the same pre-treatment time trend with our treated group.

Both SPR and IPR entrants sold products only in the Consumer Electronics category. We treat this category as the treated group in each of the two main analysis time periods. We identify a
control group (an alternate product category) for each of the marquee entrants such that there is no PR entry in the control category in the analysis time period. For the entry of the SPR, the only categories that qualify as potential control categories are Jewelry and Toys, as well as Unclassified (which is a miscellaneous catch-all category that only appears in the PU marketplace). For our main analysis, we choose Jewelry and Toys as the control category. The SPR buyers bid in only 3% of the Jewelry and Toys listings, and the buyers of Jewelry and Toys category bid in less than 0.1% of the SPR’s listings. For the entry of the IPR, the only categories that qualify as potential control categories are Appliances and Unclassified. We choose Appliances as the control category in this case. The PR buyers bid in only 0.1% of the Appliances listings, and the buyers of Appliances bid in only 0.1% of the IPR’s listings. In Appendix A.1.2, we use the Unclassified category as the control group for both the SPR entry and the IPR entry, and show that our findings are robust to this alternative control group.\(^6\) Furthermore, we affirm that the treatment and the control category listings share sufficient commonalities. In Table 3, we compare the major listing-level attributes (e.g., the retail values) between the treatment and the control groups. For all the attributes, the difference of means normalized by the standard deviation is less than 0.25, suggesting adequate balance between the groups (Ho et al. 2007).

<table>
<thead>
<tr>
<th></th>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Treatment</td>
<td>Control</td>
</tr>
<tr>
<td>Retail price per auction ($)</td>
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<td>5,959</td>
</tr>
<tr>
<td></td>
<td>(26,102)</td>
<td>(12,499)</td>
</tr>
<tr>
<td>Retail price per unit ($)</td>
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<td>33</td>
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<tr>
<td></td>
<td>(5,982)</td>
<td>(2,586)</td>
</tr>
<tr>
<td>Units per auction</td>
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<td>308</td>
</tr>
<tr>
<td></td>
<td>(2,364)</td>
<td>(1,078)</td>
</tr>
<tr>
<td>Probability of dispute per auction</td>
<td>0.146</td>
<td>0.173</td>
</tr>
<tr>
<td></td>
<td>(0.353)</td>
<td>(0.379)</td>
</tr>
<tr>
<td>Duration per auction (days)</td>
<td>3.753</td>
<td>3.650</td>
</tr>
<tr>
<td></td>
<td>(1.499)</td>
<td>(1.453)</td>
</tr>
</tbody>
</table>

Table 3. Listing comparison between treatment and control categories.

Note: 1. Diff./SD column shows the ratio of difference in corresponding treatment and control columns divided by the standard deviation of the difference. 2. Standard deviations are noted in the parentheses.

Although SPR and IPR sellers were not the only new PR entrants who sold Consumer Electronics during the contiguous 4 years covered by our observation windows, they were by far the largest and the only single-category entrants. In the PU marketplace, SPR and IPR sellers accounted

\(^6\) Appliances cannot be considered as the control category for the SPR entry because an appliance PR marketplace entered the platform only one month before the SPR entry. Jewelry and Toys cannot be considered as a control category for the IPR entry because two months after it’s entry, there was an influx of listings in Jewelry and Toys category on another PR marketplace.
for over 82% of all the consumer electronics listings on the platform during the observation period. Therefore, we select the pre-entry and post-entry analysis periods such that no other PR marketplaces with listings in the treatment category enter during this period. To further control for seasonality that may differ for the treated and the control groups (e.g., Apple releases its newer generations products in September of each year), we select the pre- and post-entry analysis periods to cover the same months of a year.\textsuperscript{7} For the SPR entry, the pre-entry period is defined as April 2012 to November 2012, and the post-entry period is April 2013 to November 2013.\textsuperscript{8} The SPR entrants gradually ramped up their supply of listings and then stabilized in June of 2013. For the IPR entry, the pre-entry period is January 2015 to May 2015, and the post-entry period is January 2016 to May 2016.\textsuperscript{9} Unlike the SPR entrant, the IPR entrant started immediately with a significant number of listings whose levels remained stable over time.

The control group exhibit a parallel trend with the treated group in the period prior to entry, which is a requirement for the difference-in-differences analysis. For visual assessment, we plot the average monthly listings per PU seller in Figure 2. The approximately parallel trends between the two groups before marquee entry supports our parallel trends assumption. Similar validity holds when looking at other metrics such as average monthly revenues per seller, total monthly listings, and total monthly revenues. A formal regression analysis is employed to establish a parallel trend in Appendix B.4.

4.2. Effects of Marquee Entry on PU Sellers’ Revenues and Supply Quantities

Our empirical specification examines the differences between the pre- and post-marquee entry period in the treated group, as compared to the corresponding difference in the control group (treatment effect). In line with our research question, we focus on the difference between this treatment effect estimate for the high- versus the low-quality PU sellers.

\textbf{Model Specification.} We specify a regression model to capture the effects of marquee entry on PU sellers of low and high qualities. The term $Y_{i,k,t}$ indicates three dependent variables for a PU seller $i$ in category $k$ and month $t$: PU seller $i$’s revenue, average normalized price (normalized price is the ratio of sale price and original retail price of a listing; we refer to this as price henceforth), and supply quantity (number of listings). $Trt_k$ is 1 if a category $k$ is the treatment group and 0

\textsuperscript{7} In Appendix A.1.3, we rerun the analysis using the entire pre-entry and post-entry periods; our findings continue to hold.

\textsuperscript{8} The pre-entry period starts in April 2012 to match the starting month of the post-entry period. The post-entry period ends in November 2013, as another marquee retailer, who lists some Consumer Electronics auctions entered in the following month.

\textsuperscript{9} The pre-entry period starts in January 2015, as a marquee retailer who specializes in Appliances launched its PR marketplace in December 2014. The post-entry period ends in May 2016 as a (relatively small) marquee retailer specializing in Consumer Electronics closed its PR marketplace the following month.
Figure 2. Avg. treated and control category PU sellers’ monthly listings around superior (left) and inferior entry (right) time period.

Note: The two vertical dashed lines specify the periods before and after the entry. PU sellers’ responses to the superior entry are a few months delayed because the PR seller started listing at intended capacity a few months after its marketplace launch. There is no delay in PU sellers’ responses after the inferior entry because the PR seller started listing in sizable quantity immediately after its marketplace launch.

otherwise. \( Post_t \) is 1 if a month \( t \) falls in a period after the focal marquee entry, and 0 if it falls in the pre-entry period. We use a binary variable \( \text{HighQuality}_i \) to describe PU seller \( i \)’s quality, indicating whether their dispute rate is lower than the median (i.e., high-quality) or not (i.e., low-quality).\(^{10}\)

\( \text{Trt}_k \times Post_t \) captures the effect on low-quality PU sellers, while \( \text{HighQuality}_i \times \text{Trt}_k \times Post_t \) captures the amount by which the entry effect on high-quality PU sellers exceeds that of low-quality PU sellers for the treated category. In addition, \( \text{HighQuality}_i \times \text{Trt}_k \) and \( \text{HighQuality}_i \times Post_t \) controls for any quality-related differences in the treated group and post-entry period, respectively.

To control for any seller idiosyncratic characteristics (such as their location and other unobservable characteristics), we use seller fixed effects, \( \eta_i \), while month fixed effects, \( \zeta_t \), control for platform-level monthly variations. All our dependent variables take positive values. As values for revenue and the number of listings include a significant number of zeroes (capturing months where seller \( i \) did not list any auctions), we employ a negative binomial regression for them.\(^{11}\) For price, which does not take zero values, we use its log transformation as the dependent variables. The regression model is specified below,

\[
Y_{i,k,t} = f \left( \beta_0^{(1)} + \gamma_0^{(1)} \text{HighQuality}_i + (\beta_1^{(1)} + \gamma_1^{(1)} \text{HighQuality}_i) \times \text{Trt}_k \right)
\]

\(^{10}\) Although the platform updates sellers’ dispute rates with every new transaction, seller quality categorization (high, low) almost never changes in our data. We therefore do not denote seller quality to be time dependent for the clarity of exposition. See Appendix B.1 for the analysis to support this claim.

\(^{11}\) We discretize monthly revenues at the $1000 level to make it a count variable.
\[ + (\beta_2^{(1)} + \gamma_2^{(1)} \text{HighQuality}) \times \text{Post}_t + (\beta_3^{(1)} + \gamma_3^{(1)} \text{HighQuality}) \times \text{Trt}_k \times \text{Post}_t + \eta_i + \zeta_t \],

where \( f \) is a negative binomial link function for revenue and number of listings regressions and an exponential link function for price regression.\(^{12}\)

**Estimation Results.** Table 4 shows the estimated effects under the SPR (IPR) entry in columns 1-3 (4-6). For the SPR entry, the insignificant coefficients on \( \text{Trt} \times \text{Post} \) in columns 1, 2, and 3 show that the effect on low-quality PU sellers’ revenues, prices, and supply is not statistically different from zero. In contrast, the coefficients on \( \text{Trt} \times \text{Post} \times \text{HighQuality} \) indicate that high-quality PU sellers enjoy a positive effect on their revenues, prices, and number of listings relative to low-quality PU sellers. Interpreting the coefficients suggests that these effects are economically significant as well. The revenues, prices, and the number of listings for high-quality PU sellers show a relative increase of $801, 0.05, and 2.5, respectively (as compared to the low-quality PU sellers).\(^{13}\) These increases represent 284%, 167%, and 189% of their average pre-entry counterparts, respectively. Taken together, this implies that the PU marketplace as a whole expanded and that high-quality PU sellers benefited more than their low-quality counterparts.\(^{15}\)

Turning to the IPR entry, the insignificant coefficients on \( \text{Trt} \times \text{Post} \) in columns 4-6 suggest no substantial effect of this entry on low-quality PU sellers’ revenues, prices, and number of listings. However, the sign on the \( \text{Trt} \times \text{Post} \times \text{HighQuality} \) is opposite to that under the SPR entry. The high-quality PU sellers show a relative decrease in their revenues and the number of listings, but no statistical change in prices. The magnitude of the revenue and listings effect is substantial. The revenues, prices, and monthly listings for high-quality PU sellers show a relative decrease of $382, 0.04, and 1.6, respectively (as compared to for the low-quality PU sellers). These changes represent 82%, 31%, and 78% of their average pre-entry counterparts, respectively. Taken as a whole, the PU marketplace experienced shrinking revenues, while the high-quality sellers bore the brunt of this shrinkage.\(^{16}\)

To convey robustness of these findings, in Appendix A.1.1, we show that entrants’ effects on PU sellers’ supply and revenues remain similar under alternative quality specifications (e.g., when only the top 25% of PU sellers are defined as of high-quality; when using the dispute rate linearly in the regression model rather than categorizing it in a binary format of high and low). In addition,\(^{12}\)

\(^{12}\) \( \gamma_0^{(1)} \) and \( \beta_2^{(1)} \) are not identified due to fixed effects.

\(^{13}\) 0.05 is the increase in the normalized price; recall that this is the ratio of the sale price to the original retail price of a listing

\(^{14}\) These are marginal effects, which are computed by averaging the effect size over all co-variate values in the data.

\(^{15}\) Appendix B.5 provides analysis showing the average effect on the overall PU marketplace.

\(^{16}\) See Appendix B.5 for the average effect on the entire PU marketplace.
<table>
<thead>
<tr>
<th></th>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Revenue</td>
<td>Log(Price)</td>
</tr>
<tr>
<td>Trt × Post × HighQuality</td>
<td><strong>1.983</strong> (0.941)</td>
<td><strong>1.107</strong> (0.446)</td>
</tr>
<tr>
<td>Trt × Post</td>
<td>-0.182 (0.755)</td>
<td>-0.458 (0.328)</td>
</tr>
<tr>
<td>Trt × HighQuality</td>
<td>-1.325* (0.681)</td>
<td>-0.633* (0.373)</td>
</tr>
<tr>
<td>Post × HighQuality</td>
<td>-1.765** (0.850)</td>
<td>-0.321 (0.384)</td>
</tr>
<tr>
<td>PU Seller Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Month Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
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<tr>
<td>Adjusted R²</td>
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<td></td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-542.435</td>
<td>-820.022</td>
</tr>
</tbody>
</table>

Notes: *p<0.1; **p<0.05; ***p<0.01

Table 4. Entrants’ heterogeneous effects on PU sellers

Note. 1. Price is normalized and refers to the ratio of the sale price of a listing to its original retail price. It is missing if a given PU seller does not list any auctions. Therefore, the number of observations for the price regression (Columns 2 and 5) are fewer than those of the revenue and listing regressions. 2. Standard errors are noted in the parentheses.

in Appendix A.1.4, we examine the entry effect on other listing features (e.g., number of items in the listing, retail value of a listing) and find no statistically significant change. This suggests that changing the number of listings is the primary lever a PU seller uses to strategically change their supply. We also find that the marquee entries have no statistically significant effect on the number of PU sellers who enter and exit (see Appendix A.1.5). PR sellers’ exogenous entry times and the relatively stable entry/exit patterns indicate a comparable environment before and after entry and that our analysis is not driven by a specific (biased) group of sellers who remain on the PU marketplace after the marquee’s entry.

The above findings affirmatively answer both of the research questions posed in the Introduction. We find that high-quality and low-quality PU marketplace seller revenues and supply quantities are differentially impacted, and that the sign and magnitude of the effect critically depends on marquee entrant quality. In particular, our findings imply that, while the SPR’s entry results in the high-quality PU sellers being better off relative to their low-quality peers, the IPR’s entry leaves high-quality PU sellers relatively worse off. A corollary of this analysis is the effect on overall PU marketplace listing quality; given that the SPR versus IPR entry leads to differential supply quantity changes by high- and low-quality PU sellers, we see that the average PU marketplace
supply-quality shifts in the direction of the entrant quality. When the SPR joins, the fraction of high-quality listing in the PU marketplace increases from 69.1% to 92.4%. In contrast, when the IPR joins, the fraction of high-quality listings on the PU marketplace decreases from 57.9% to 31.7%.

The inclusion of a marquee seller on the platform not only affects the quality of the platform directly via the entrant’s quality, but, as shown above, also has a substantial indirect effect via its effect on PU sellers. Marquee entrants exaggerate the shift of platform quality in the direction of their quality. If a platform does not incorporate this externality, it may set itself on an unanticipated cycle of growth skewed towards one end of the quality spectrum.

Our findings regarding the marquee entrants’ overall effect on PU sellers naturally leads us to try to gain a deeper understanding of the mechanisms behind these effects. Since the fates of sellers within and across marketplaces are intertwined due to their shared buyer pool, the following analysis looks closely at the buyers’ behaviors, which, in turn, will guide us towards the mechanism behind the effects described above.

4.3. Buyer Analysis
In this section, we will show that buyers’ behaviors (in particular, their quality sensitivity) are key drivers of the revenue and supply effects we observed above. Towards this end, we examine (sequentially) the participation and bidding behaviors of PU and PR buyers, respectively (recall that PU (PR) buyers are those who first registered in the PU (PR) marketplace). We will first show how PU buyers’ participation changes in PU listings after PR entry and how PR buyers’ participation in PU listings depend on PR entrant quality. These effects lead to localized market stealing and localized market expansion phenomena for PU sellers. In §4.3.1 and §4.3.2, we illicit these effects based on a proxy buyer quality sensitivity measure. In §4.3.3, we precisely measure buyer quality sensitivity for a subset of data and validate our observations.

4.3.1. Localized Market Stealing. Localized market stealing occurs when the marquee entrant attracts PU buyers away from quality-neighboring PU sellers. To check for the presence of localized market stealing, we first examine the participation of PU buyers in PU and PR listings for the treated category. To examine the behavior through the lens of quality sensitivities, for each buyer $j$, we compute their (percentage) participation in high-quality PU sellers’ listings before the focal entry, and denote it by $PctHighQualityParticipated_j$. This serves as a proxy for buyers’ preferences for quality sellers (i.e., quality sensitivity). PU buyers who participate in relatively more high-quality PU seller listings are deemed to be more quality sensitive PU buyers, while those whose participation is relatively less are deemed to be less quality sensitive. Admittedly, this is an imperfect proxy, and therefore we will return to capturing quality sensitivity with precision in
§4.3.3. We note that PU buyers are consistent in their quality sensitivities between the before and after entry periods. A buyer with higher \( \text{PctHighQualityParticipated} \) is more likely to participate in high-quality than low-quality PU listings in the post-entry period.\(^{17}\)

The dependent variable \( \text{ParticipatePU}_{j,t} \) is a dummy variable indicating if a PU buyer \( j \) participated in any PU listings in month \( t \). \( \text{Post}_t \) is a dummy variable denoting the post-entry period. The focal independent variable is \( \text{Post}_t \times \text{PctHighQualityParticipated}_j \), which captures the difference in PU buyers’ participation behaviors based on their preferences for higher-quality sellers.

To control for buyer idiosyncratic characteristics, we use buyer fixed effects, \( \nu_j \).\(^{18}\) These fixed effects also restrict our estimation to buyers who are present in both the pre- and post- periods, alleviating buyer selection effects potentially confounding our estimates. We also control for buyers’ tenure (in months) on the platform.

To account for supply level changes that might differentially affect buyers based on their quality sensitivities, we apply supply level controls. To do so, the focal category (Consumer Electronics) is divided into three sub-categories (cell phones, computers/laptops, and others – including tablets and gaming consoles). \( P_t \) denotes the number of PU listings in month \( t \) for each of these subcategories. We control for \( P_t \) and \( P_t \times \text{PctHighQualityParticipated}_j \), which allows the control effect to vary with buyer quality sensitivity.\(^{19}\) We also control for time effects using month fixed effects. \( Z_{j,t} \) collectively denotes the control variables specified above (i.e., buyers’ tenure, \( P_t \) and \( P_t \times \text{PctHighQualityParticipated}_j \), month fixed effects); we will re-use these in our subsequent buyer-level analyses. We note that our results are robust whether or not we control for \( Z_t \).

The (logistic) regression model is given by

\[
\text{logit}[\Pr(\text{ParticipatePU}_{j,t} = 1)] = \beta_{0}^{(2)} + \gamma_{1}^{(2)} \text{Post}_t \times \text{PctHighQualityParticipated}_j + \beta_1^{(2)} Z_{j,t} + \nu_j.
\]

To complement the above analysis, we examine PU buyers’ participation in PR marketplace listings. Localized market stealing effects in the PU marketplace should imply relatively higher (lower) participation of quality-sensitive PU buyers in the SPR (IPR) marketplace. Verifying this also helps us rule out an alternative explanation that the suggested localized stealing effect on PU sellers is due to buyer attrition from the platform. Note that analyzing PU buyers’ participation in the PR marketplace is only meaningful in the post-period (i.e., the period after the entry takes

\(^{17}\) Appendix A.3.4 provides supporting analysis based on the quality-sensitivity estimation setup in §4.3.3.

\(^{18}\) These buyer fixed effects absorb the direct effect of \( \text{PctHighQualityParticipated}_j \) and hence \( \text{PctHighQualityParticipated}_j \) is not controlled for.

\(^{19}\) We did not/could not use these controls in the analyses in Section 4.2 due to the presence of seller fixed effects there. The unit of analysis here is buyer×month as compared to the seller×category×month unit used earlier.
place). \(ParticipatePR_{j,t}\) is the dependent variable, which denotes whether a PU buyer \(j\) has participated in any of the new entrant listings in month \(t\). \(PctHighQualityParticipated_j\) is the focal independent variable of interest. We use the same set of controls, \(Z_{j,t}\), as before. We cannot control for buyer fixed effects anymore, as they would absorb the effect of interest. Instead, \(x_j\), which is defined as the average monthly number of auctions participated in by a buyer in the pre-entry period, is used to control for some buyer-level differences.\(^{20}\) The (logistic) regression model for this analysis is given by

\[
\text{logit}[Pr(\text{ParticipatePR}_{j,t} = 1)] = \beta_0^{(3)} + \beta_1^{(3)} PctHighQualityParticipated_j + \beta_2^{(3)} Z_{j,t} + x_j. \tag{3}
\]

<table>
<thead>
<tr>
<th>(Post \times PctHighQualityParticipated)</th>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) PU</td>
<td>(2) PR</td>
<td>(3) PU</td>
</tr>
<tr>
<td>(-1.070^{**})</td>
<td>(1.142^{***})</td>
<td>(0.442)</td>
</tr>
<tr>
<td>(1.462^{*})</td>
<td>(-1.212^{***})</td>
<td>(0.747)</td>
</tr>
<tr>
<td>(PctHighQualityParticipated)</td>
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<td>(-0.038)</td>
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<td>(Tene)</td>
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<td>(0.120)</td>
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<tr>
<td>(Avg. \text{ Participated Auctions} (x))</td>
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<td>(0.041^{***})</td>
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<td>Buyer Fixed Effects</td>
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<td>Log Likelihood</td>
<td>(-5,206.260)</td>
<td>(-1,227.227)</td>
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</table>

\(Note:\) \(*p<0.1; \; **p<0.05; \; ***p<0.01\)

**Table 5. PU buyers’ participation in PU and new entrants’ listings.**

Note: Columns denoted by PU refer to ParticipatePU and by PR refer to ParticipatePR.

Table 5 shows the estimates of Regressions (2) and (3) for both the SPR and IPR entries. For the SPR entry, the negative coefficient of \(Post_t \times PctHighQualityParticipated_j\) in column 1 indicates that PU buyers with higher quality sensitivity decrease their participation in PU listings by a larger amount. Column 2 supports this; we find that PU buyers with higher quality sensitivity are more inclined to participate in the entrant’s listings. For the IPR entry, we see an opposite pattern: Column 3 indicates that PU buyers’ participation decrease in PU listings is significantly

\(^{20}\) In Appendix A.2.1, we verify that buyers’ pre-entry monthly number of bids is sufficient to control for buyer-level differences. We re-estimate \(\gamma_1^{(3)}\) in Regression (2) with this replacement and find similar results.
These findings are consistent with the fact that an entrant increases competitive pressure by attracting some buyers from the PU sellers. However, also of particular interest is how this pressure unfolds across PU sellers of differing qualities. The entry of the SPR hurts high-quality PU sellers more by luring away quality sensitive PU buyers, while the entry of the IPR hurts low-quality PU sellers more by luring away less quality sensitive PU buyers who had predominantly shopped from them before. Since the competition effects of an entrant are particularly salient for PU sellers who are neighbors to the entrant in terms of quality, this confirms the existence of a localized market stealing effect.

This stealing effect stands in stark contrast to our observations in §4.2 that quality-neighboring PU sellers had a relative boost in revenue and supply quantity after an entrant joins. That is, the localized market stealing effect is unable to explain the observed revenue and supply outcomes for sellers of high and low qualities. We next examine the behaviors of PR buyers who join alongside the PR entrant, which helps us bridge the gap in our findings.

4.3.2. Localized Market Expansion. Localized market expansion is the relative increase in revenues of its quality-neighboring PU sellers. To check for the presence of localized market expansion, we examine the participation of PR buyers in PU listings for the treated category and the post-entry period by comparing PR buyers’ participation in high-quality ($\theta_H$) and low-quality ($\theta_L$) PU sellers’ listings. Unlike previous analyses where we distinguished buyer behaviors by $\text{PctHighQualityParticipated}_j$, here we distinguish the behaviors of (PR) buyers by SPR and IPR buyers.\footnote{In Appendix A.2.2, we show that the findings are robust to classifying PU buyers discretely into high and low quality sensitivity types as opposed to the continuous measure used above.} We let the binary variable $\text{HighQualityListing}_\theta$ denote high-quality listings; it takes the value of 1 when $\theta = \theta_H$, and is 0 otherwise. $\text{Listing}_\theta$ denotes the set of listings from PU sellers with the same quality (i.e., same $\text{HighQualityListing}_\theta$). $\text{ParticipatePU}_{\theta,j,t}$ is our dependent variable, which indicates whether or not a PR buyer $j$ participates in any listing in set $\text{Listing}_\theta$ for $\theta \in \{\theta_H, \theta_L\}$ in month $t$. We use buyer fixed effects $\nu_j$ as well as the same set of controls as in the previous subsection ($Z_{j,t}$). The regression model is specified as

$$\logit[\Pr(\text{ParticipatePU}_{\theta,j,t} = 1)] = \beta_0^{(4)} + \beta_1^{(4)} \text{HighQualityListing}_\theta + \beta_2^{(4)}'Z_{j,t} + \nu_j.$$ (4)

A positive coefficient for $\text{HighQualityListing}_\theta$ would indicate that PR buyers disproportionately participate in high-quality PU listings. Table 6 reports the regression results for the SPR and IPR

\footnote{$\text{PctHighQualityParticipated}_j$ was defined for PU buyers based on their pre-entry behaviors and therefore cannot be applied to PR buyers.}
entries, respectively. We find that the coefficient on $\text{HighQualityListing}_e$ is statistically significant and opposite for the two entries. The positive (negative) coefficient for the SPR (IPR) entry suggests that the SPR (IPR) buyers participate relatively more (less) in high-quality PU marketplace sellers’ listings. We note that the results are robust when we model buyers’ participation for individual sellers rather than for a set of high- or low-quality sellers (see Appendix A.3.1). In other words, PR buyers participate more in the listings of quality-neighboring PU sellers to the entrant and results in localized market expansion.

<table>
<thead>
<tr>
<th></th>
<th>(1) Superior Entry</th>
<th>(2) Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Participate PU</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{HighQualityListing}$</td>
<td>1.098***</td>
<td>−1.618***</td>
</tr>
<tr>
<td></td>
<td>(0.356)</td>
<td>(0.344)</td>
</tr>
<tr>
<td>$\text{Tenure}$</td>
<td>−0.715</td>
<td>0.390</td>
</tr>
<tr>
<td></td>
<td>(0.624)</td>
<td>(0.552)</td>
</tr>
<tr>
<td>Buyer Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Month Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Supply Assortment Controls</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>2,076</td>
<td>2,792</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>−800.293</td>
<td>−1,131.617</td>
</tr>
</tbody>
</table>

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Table 6. PR buyer participation in the PU marketplace.

The localized nature of market expansion suggests that buyers brought in by an entrant do have a higher- or lower-quality sensitivity, and that the sensitivity is correlated with the quality of the entrant. Those brought in by the SPR entrant appear to be more quality sensitive and thus prefer to shop with high-quality PU sellers. This is despite high-quality listings having higher prices (33% higher on average). The opposite is true for buyers brought in by the IPR entrant.

The localized market expansion effect is in the direction of the revenue and supply effect we saw in §4.2: PU sellers neighboring in quality to the PR entrant experience a relative boost in revenue and supply quantity upon their entry. In our theory section, §5, Proposition 2 will highlight that this localized nature of the market expansion is the key driver of the revenue and supply changes we observe. A market expansion that is not localized does not result in the asymmetric revenue and supply response that we have empirically observed.

Given that from whom a buyer chooses to buy is a combination of their quality sensitivity and other factors (price and listing attributes being prominent), we take a closer look at buyers’ behaviors to investigate the assertion that PR buyers’ quality sensitivity is positively correlated with the entrant quality. To do so, we focus our analysis on a subcategory for which there is a
greater level of consistency and detail across all listings. For this subcategory we examine buyers’ bids (instead of just participation) in an auction and control for a more comprehensive set of listing features.

4.3.3. Buyers’ Quality Sensitivity Comparison. Our focal platform and associated proprietary data set possess the advantage of having rich buyer-level information when compared to a typical e-commerce platform. We are able to observe bidders’ behaviors across a range of auction listings and marketplaces over time to estimate a buyers’ quality sensitivities. For identification, we use the variation within a buyers’ bids across PU listings of different qualities. To prevent any listing characteristics other than quality influencing our quality sensitivity estimates, we focus on listings of iPhones where controls are relatively comprehensive since all iPhone listings state the model number (e.g., iPhone 4, 5, or 6), network carriers (e.g., AT&T), and condition information (e.g., new, used, salvaged). We will therefore analyze buyers’ bids for iPhone auctions and determine how the quality sensitivities of the PR buyers depends on the entrant quality and how these quality sensitivities compare with that of PU buyers.\footnote{In addition, better controls also improve the efficiency of our estimates. Using simulated data, we demonstrate - in Appendix B.6 - the importance of including detailed product information in identifying quality sensitivity.}

Our dependent variable is a buyers’ bid divided by the listing’s retail value, denoted by $Bid_{i,j,\ell,t}$ (for PU seller $i$, buyer $j$, auction $\ell$, and month $t$).\footnote{When a buyer bids on the same listing multiple times, we use their last bid in the analysis.} We control for the iPhones’ models, carriers, conditions, and per-unit retailer prices, as well as each listing’s lot size (number of iPhone units), in vector $X_{i,\ell}$. The term $Is_{PR\text{buyer}}_j$ indicates whether a buyer is a PR ($=1$) or a PU buyer ($=0$); the interaction-term $Is_{PR\text{buyer}}_j \times X_{i,\ell}$ allows PR and PU buyers’ to have different valuations for the product features. To control for any buyer, seller, and time level unobserved factors, we add fixed effects for buyers ($\nu_j$), sellers ($\eta_i$), and months ($\zeta_t$). The regression model we use is specified as

$$Bid_{i,j,\ell,t} = \beta_0^{(5)} + \gamma_0^{(5)} Is_{PR\text{buyer}}_j + (\beta_1^{(5)} + \gamma_1^{(5)} Is_{PR\text{buyer}}_j) \times HighQuality_\ell$$

$$+ (\beta_2^{(5)} + \gamma_2^{(5)} Is_{PR\text{buyer}}_j)’ \times X_{i,\ell} + \nu_i + \eta_j + \zeta_t + \epsilon_{i,j,\ell}. \hspace{1cm}(5)$$

Table 7 presents the estimates.\footnote{Some of the coefficients are not estimated due to fixed effects (Intercept, $Is_{PR\text{buyer}}$, and $HighQuality_\ell$).} We find that PR buyers exhibit significantly different quality sensitivities than do the PU buyers. The SPR buyers are significantly more quality sensitive than PU buyers ($\gamma_1^{(5)} = 0.029$), while the IPR buyers are significantly less quality sensitive than PU buyers ($\gamma_1^{(5)} = -0.052$).\footnote{The identified sensitivity differences are robust and highly statistically significant in many of the cases when considering alternative quality specifications for PU sellers (see Appendix A.3.2). Moreover, we find consistent estimates when analyzing buyers’ participation decisions rather than bid values (see Appendix A.3.3).} This analysis sheds light on why the market expansion for PU sellers due
to entrant is localized; entrants bring in like-minded quality buyers. While the extant marketplaces literature has shed light on the positive cycle of growth, we find the effect to be more nuanced, while also intuitive. New sellers on the platform attract buyers who have a preference for the quality-type of these added sellers: High-quality entrants beget more quality-sensitive buyers, while low-quality entrants beget less quality-sensitive buyers. The localized market expansion and stealing competition that ensues determines the eventual (relative) winners and losers. Our results indicate that the positive or negative impacts of competition very much depends on whether the PU seller is neighboring (in quality) to the entrant.

Our empirical analysis has shed light on (i) the effect of PR entrant quality on revenues and supply of PU sellers (of high and low qualities), (ii) localized market stealing and expansion, and (iii) how localized market expansion is, in turn, driven by the quality sensitivities of buyers brought in by the entrants. However, a few questions still remain, which the empirical analysis cannot help us answer. First, why is there an asymmetric PU supply response based on PU sellers’ quality? Second, would we continue to observe the same asymmetric revenue and supply effects on PU sellers if PR buyers’ quality sensitivities were independent of the entrant’s type? Finally, how much of the asymmetric revenue effect is driven by PU sellers’ supply reactions, and how much is a result of other competition factors? This is perhaps a particularly relevant consideration as there are several marketplaces where a seller’s ability to change supply is quite constrained. On one hand, several platforms in the gig economy allow sellers to flexibly change their supply quantities (e.g., the ability of a driver to determine how much to drive on Uber). On the other hand, supply could be constrained on platforms such as Airbnb, where sellers only have a limited number of units they can list or brick-and-mortar settings where shelf spaces are limited in the short-term. Would our findings generalize to these supply constrained settings? To investigate these questions, we explore our research questions using a stylized theory model in the following section.

\[ \text{Bid} = \beta_0 + \beta_1 \text{Is\_PR\_buyer} \times \text{HighQuality} + \sum \text{Other\_Factors} + \epsilon \]

Table 7. Quality sensitivity comparisons between PR buyers and PU buyers.
5. Robustness of Empirical Findings - A Stylized Model

To identify the drivers of entrants’ supply and demand effects and to address our remaining questions posed above, we propose a stylized game-theoretical model. The model integrates the two competing localized demand effects and describes sellers’ supply reactions. Motivated by the online B2B liquidation platform, the model characterizes sellers’ and buyers’ equilibrium behaviors before and after a given marquee entry. It features heterogeneity in sellers’ qualities and buyers’ quality sensitivities. We show that its predictions on buyers and sellers’ behaviors under the superior and inferior entries (Observations 1 and 2) are consistent with the empirical findings described in the preceding sections. Hence, the model is empirically validated.

The empirical evidence was based on two specific scenarios – specific demand and supply realizations associated with each entrant – which renders limited insights into the underlying mechanisms. The theoretical model generalizes the empirical results by investigating counterfactual scenarios (e.g., what if the quality sensitivities of buyers brought in by the entrants are not different from those of existing buyers) and offers insight into the rationale behind buyers’ and sellers’ reactions (Propositions 1, 2, and 3). It allows us to explore which factors drive sellers’ supply expansion and revenue outcomes that create the winners and losers we have observed empirically.

The model captures the following platform elements: (i) The presence of a PU marketplace that hosts sellers of different qualities and a pool of PU buyers with heterogeneous quality sensitivities; (ii) The entry of a PR seller with an exogenous quality, who brings along a pool of PR buyers to the platform; (iii) Sellers who optimize their revenues by competing in supply (i.e., Cournot competition) before and after the entry, and buyers who choose the sellers with whom to transact so as to maximize their utility. These essential features help us operationalize localized market stealing and expansion effects and the resulting equilibrium adjustments in PU sellers’ supply and revenues.

The model has two discrete time periods denoted by $t$: $t = 0$ denotes a platform with only a PU marketplace (buyers and sellers). At $t = 1$, a PR entrant joins the platform while also bringing in PR buyers. We model two PU sellers, one high-quality ($\theta_H$) and one low-quality ($\theta_L$), as well as one PR entrant (of quality $\theta_E$). Each sellers’ marginal supply costs are normalized to 0; sellers decide their supply quantities, $Q_{i,t}$, and the resultant price(s), $p_{i,t}$, are a result of the Cournot competition. Sellers maximize their individual revenues $\pi_{i,t} = p_{i,t}Q_{i,t}$ in each time period.

There is a continuum of buyers each of whose demand is infinitesimally small. The total mass of demand of PU buyers is 1 (normalized), and of PR buyers is $\mu$. We focus on scenarios that PR buyers mass is sizable but less than the PU buyers (i.e., $0.9 \leq \mu < 1$), to reflect our empirical setting.

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28 Literature (Bulow and Klemperer (1998), Klemperer (2004) (Chapter 2.5)) has shown some equivalence in auction and oligopoly competition models.
A key aspect of the buyer model is that buyers differ in their quality sensitivities, with some buyers willing to pay a premium price for higher quality. We capture this using the following utility model for buyers: Let $x$ be uniformly distributed in the interval $[0, 1]$. The utility of a PU buyer $x$ who purchases from seller $i$ of quality $\theta_i$ at price $p_{i,t}$ is given by

$$U_{PU}(x, \theta_i, p_{i,t}) = (x\theta_i - p_{i,t}) \cdot 1\{\text{transact with seller } i\}, \quad (6)$$

where $x\theta_i$ stands for the buyer’s willingness to pay (WTP) for seller $i$’s product. The utility of choosing the outside option is normalized to 0.

The utility specification for PR buyers allows them to have different quality sensitivities when compared to PU buyers. We define the utility for PR buyer $y$ who purchases from seller $i$ of quality $\theta_i$ at price $p_{i,t}$ to be given by

$$U_{PR}(y, \theta_i, p_{i,t}) = (y\theta_i^\alpha - p_{i,t}) \cdot 1\{\text{transact with seller } i\}. \quad (7)$$

Here, $\alpha$ captures the difference in PU and PR buyer quality sensitivities, while $y$, similar to $x$, is uniformly distributed in $[0, 1]$ to model heterogeneity among these buyers, and $y\theta_i^\alpha$ is the buyer’s WTP for seller $i$’s product. The utility of choosing the outside option is normalized to 0.

Note that for $\theta_i > 1$ for $i \in \{L, H, E\}$, $\alpha > 1$ ($\alpha < 1$) can capture that PR buyers are more (less) quality sensitive than PU buyers (i.e., $\theta_i^\alpha > \theta_i$ ($\theta_i^\alpha < \theta_i$)). Thus, without loss of generality, we assume $\theta_i > 1$ for $i \in \{L, H, E\}$ to allow $\alpha$ to capture quality sensitivity, and let $\alpha$ assume values within a unit-length interval centered at 1 (i.e., $\alpha \in [0.5, 1.5]$). In the subsequent analysis, we will analyze the entry of sellers who are of either much higher or much lower quality than PU sellers (i.e., a superior and inferior entrant) to reflect the nature of entrants in our empirical analysis. Consistent with the data, we assume that $\theta_E > \theta_H > \theta_L$ for a SPR (IPR) entrant. As shown by Table 7, PR buyers’ quality sensitivities are aligned with the entrants’ qualities: PR buyers of the SPR (IPR) entrant are significantly more (less) sensitive to quality than PU buyers. Therefore, we assume that $\alpha$ is sufficiently larger than 1 (i.e., $\alpha \to 1.5$) under the SPR entry, while $\alpha$ is sufficiently smaller than 1 (i.e., $\alpha \to 0.5$) under the IPR entry.\(^{31}\)

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\(^{29}\) Note that a value of $\mu$ that is too low does not allow for a sufficient entrant-created market expansion effect, which played a pivotal role in our empirically explaining PU seller revenue and supply changes.

\(^{30}\) The exact quality preference $\alpha$ and size $\mu$ of entrant bought buyers would depend on entrant specific exogenous parameters such as their brand popularity, marketing efforts, etc., factors which are outside the scope of this paper. We therefore take $\alpha$ and $\mu$ as exogenously given.

\(^{31}\) Note that a value of $\alpha$ that is too low or too high may lead to behaviors that are not representative of our empirical setting. In either of these cases, the PR buyers would minimally bid/purchase from PU marketplace sellers marginalizing the externality of the entrant on PU sellers that we intend to study. This drives our assumptions on $\alpha$ above.
Lastly, we exclude the cases where PU and PR buyers’ quality preferences are either
indistinguishable (i.e., $\theta_i^\alpha \rightarrow \theta_i$ when $\theta_i$ approaches 1) or widely separated (i.e., no overlap between
PU and PR buyers’ seller choices when $\theta_i$ is very large) by assuming that $\theta_i$, $i \in \{L, H, E\}$ are
sufficiently greater than 1 but not too large. Appendix D.1 provides a complete characterization
of the assumptions. In Appendix D.3, we numerically evaluate the robustness and boundaries of
our analytical findings by relaxing our assumptions regarding range of values that $\alpha$, $\mu$ and $\theta$ can
take.

Market Equilibrium Outcomes. We focus on pure-strategy Nash equilibrium of the supply-
demand game before and after an entrant joins. The following set of equilibrium conditions hold:
Each seller optimizes on their supply quantity, $Q_{i,t}$, given a price that is a function of their supply
quantities, $Q_{i,t}$, as well as those of their competitor’s total supply quantity, $Q_{-i,t}$. The optimal
quantities satisfy

$$Q_{i,t}^* = \arg \max_{Q_{i,t}} Q_{i,t} \cdot p_{it}(Q_{i,t}, Q_{-i,t}^*).$$

Given each seller’s quality and price, each buyer chooses a seller or the outside option to maximize
their utility. In particular, PU and PR buyers’ optimal choices are given by

$$\arg \max_{i \in S_t} U_{PU}(x, \theta_i, p_{it}), \forall t \in \{0, 1\}, \text{ and } \arg \max_{i \in S_t} U_{PR}(y, \theta_i, p_{i,1}),$$

where $S_0 = \{L, H, \emptyset\}$ and $S_1 = \{L, H, E, \emptyset\}$. Let $X_{i,t}^*$ and $Y_{i,t}^*$ be the PU and PR buyer sets parameterized by $x$ and $y$, whose optimal choice is seller $i$. That is,

$$X_{i,t}^* = \{x | i = \arg \max_{i \in S_t} U_{PU}(x, \theta_i, p_{it})\} \text{ and } Y_{i,t}^* = \{y | i = \arg \max_{i \in S_t} U_{PR}(y, \theta_i, p_{i,1})\}. \quad (8)$$

Equilibrium prices are formed to match the seller supply and demand. In other words, $p_{i,t}$ satisfies
the following market-clearing conditions $\forall i \in \{L, H, E\}$

$$Q_{i,t}^* = \lambda(X_{i,t}^*) + 1 \{t = 1\} \cdot \mu \cdot \lambda(Y_{i,t}^*), \quad (9)$$

where $\lambda(\cdot)$ denotes the mass of a given buyer set.

5.1. Model Analysis
As a first step towards answering the questions posed at the end of the previous section, we verify
and validate with Observations 1 and 2 that our model captures critical empirical observations
upon a marquee entry. To do so, we confirm that our model’s equilibrium characterizations are
aligned with the empirical findings in Sections 4.3.1 and 4.3.2. After validating the model, we
then explore counterfactuals uncovering the role of PU seller supply flexibility (Proposition 1) and
PR buyer quality preferences (Proposition 2) on the equilibrium outcomes. Finally, we present a
counterfactual analysis when an entrant is of an intermediate quality (Proposition 3).
Observation 1. In equilibrium, we observe both a localized market stealing effect as well as a localized market expansion effect. That is, a quality-neighboring PU seller loses more PU buyers to the entrant and attracts more PR buyers than a quality-distant PU seller, upon a marquee entry (Superior or Inferior).

All the proofs as well as a complete equilibrium characterisation are shown in Appendix D. At $t = 0$, PU buyers can be labeled as either being quality sensitive (with a preference for the high-quality ($\theta_H$) seller) or quality insensitive (with a preference for the low-quality ($\theta_L$) seller). The heterogeneity amongst the PU buyers, and their resulting preferences for the $\theta_H$ or $\theta_L$ seller, is a key driver of the localized stealing effect upon an entry. When an SPR joins, $\theta_H$’s buyers value the high quality from this entrant much more than do $\theta_L$’s buyers. This leads to higher-quality-sensitive buyers disproportionately switching to the entering (PR) seller, yielding a much higher loss for the $\theta_H$ (than $\theta_L$) seller. Opposite dynamics unfold when an IPR joins leading to a much higher loss for the $\theta_L$ seller. In either of the scenario, a localized market stealing takes place due to the entrant. When compared to the PU buyers, the SPR (IPR) buyers are more (less) quality sensitive. Therefore, it is no surprise that $\theta_H$ gains more new buyers when an SPR enters, while $\theta_L$ gains more new buyers when an IPR enters. This is the localized market expansion effect.

In addition to the buyers’ preferences for quality and hence sellers, PU sellers are able to adjust their supply quantities (and hence resulting prices) in the face of a new entrant. The following proposition outlines the differential effect on supply quantity and revenues of $\theta_H$ and $\theta_L$ sellers from the PR entrant.

Observation 2. The equilibrium ratio of supply from $\theta_H$ relative to $\theta_L$, as well as the equilibrium revenues, is larger (smaller) after a superior (inferior) marquee enters. Formally, $Q_{H,1}/Q_{L,1} > Q_{H,0}/Q_{L,0}$ and $\pi_{H,1}^*/\pi_{L,1}^* > \pi_{H,0}^*/\pi_{L,0}^*$ after a superior entry, and $Q_{H,1}/Q_{L,1} < Q_{H,0}/Q_{L,0}$ and $\pi_{H,1}^*/\pi_{L,1}^* < \pi_{H,0}^*/\pi_{L,0}^*$ after a inferior entry.

Upon a marquee entry, PU sellers have an incentive to expand their supply; however, the incentives are not equal across all sellers. In response to the entry of SPR, $\theta_H$ can expand its supply (and decrease its price) to help alleviate some market stealing effects as well as encourage PR buyers to shop with them. The same is not true for $\theta_L$, as the effects of entry are diminished due to quality-distance. Therefore, both stealing and expansion effects incentivize $\theta_H$ to expand supply relatively more than $\theta_L$ when facing a superior entrant. Despite a decrease in prices due to increased competition, the supply effect is stronger and revenues for $\theta_H$ change in the direction of supply quantity. We find that the same set of dynamics yield reversed results upon the entry of an inferior entrant.

In addition to the competition across the PR and PU sellers, Observation 2 incorporates the peer competition amongst PU sellers. Peer competition always favors $\theta_H$ since its product dominates
θ_L’s product if offered at the same price. Consequently, θ_L has to reduce its price to at least $(θ_H^* − θ_L^*)y$ below θ_H’s price to attract PR buyer $y$. It is easier for θ_H to cannibalize θ_L’s market via supply expansion than the other way around. In other words, peer competition encourages θ_H to expand its market share relative to θ_L regardless of the entrant’s type. Despite θ_L’s disadvantage, Observation 2 highlights the possibility that θ_L can still expand its market share relative to its high-quality peer when the inferior entrant joins with quality insensitive PR buyers. Furthermore, Observation 2 establishes that the neighboring PU seller’s revenue is always better off than the distant one, regardless of entrant type.

The above observation also leads to a direct but important corollary regarding PU marketplace quality dynamics as a result of a marquee’s entry.

**Corollary 1.** The average quality of supply on the PU marketplace increases (decreases) upon a superior (inferior) marquee entry.

**Mechanism and Extensions.** As noted at the end of the previous section, it is worth disentangling the contribution of supply response to the identified asymmetric revenue outcomes that flip based on the quality of the entrant. That is, while Observation 2 identifies revenue and supply outcomes when sellers are able to strategically adjust supply in response to a new entrant, we wish to isolate the importance of supply response by characterizing equilibrium revenues post-entry under the assumption that PU sellers cannot adjust supply levels in response.

**Proposition 1.** Consider a PU marketplace where sellers cannot adjust their supply post PR-entry (denoted by NR; i.e., non-responsive). The equilibrium ratio of revenues of θ_H relative to θ_L is smaller (larger) after a superior (inferior) marquee enters. Formally, $\frac{π_{H,1,NR}}{π_{L,1,NR}} < \frac{π_{H,0}^*}{π_{L,0}^*}$ after a superior entry, and $\frac{π_{H,1,NR}}{π_{L,1,NR}} > \frac{π_{H,0}^*}{π_{L,0}^*}$ after an inferior entry.

Proposition 1 states that in a market where PU sellers are unable to adjust supply in response to entry, the quality-neighboring PU seller will be worse off than the quality-distant seller. This proposition, combined with Observation 2 suggests that the quality-neighboring PU seller can reverse this negative effect by adjusting their supply. Therefore, a PU seller’s strategic supply reaction plays a pivotal role in bringing about the localized market expansion in the presence of an entrant.

Proposition 1 also finds support in Zervas et al. (2017)’s empirical findings regarding the impact that Airbnb’s entry have on hotel revenues. Airbnb’s entry into the short-term lodging market is synonymous with a low-quality entrant in our setting, as it comprises of a large number of economy accommodations. Further, the hotels cannot quickly change their room supplies in rapid response to Airbnb entries. Consistent with our proposition above, Zervas et al. (2017) find that quality-neighboring hotels to Airbnb (i.e., budget/economy) are worse off than those of distant quality (i.e., luxury/upscale).
We now investigate one of the other key drivers of our findings in Observation 2. In particular, we turn to a question posed at the end of the previous section; namely, would we continue to observe the same asymmetric revenue and supply effect on PU sellers if PR buyers’ quality sensitivities were independent of the entrant’s type? To study this, we compare our results above with a setting where \( \alpha = 1 \) for both the SPR and IPR entries. This is equivalent to assuming that PR buyers are similar (in WTP distribution) to PU buyers.

**Proposition 2.** If \( \alpha = 1 \), the equilibrium ratio of supply from \( \theta_H \) relative to \( \theta_L \), as well as the equilibrium revenues, remain the same (are larger) after a superior (inferior) marquee enters. Formally, \( Q_{H,1}^*/Q_{L,1}^* = Q_{H,0}^*/Q_{L,0}^* \) and \( \pi_{H,1}^*/\pi_{L,1}^* = \pi_{H,0}^*/\pi_{L,0}^* \) after a superior entry, and \( Q_{H,1}^*/Q_{L,1}^* > Q_{H,0}^*/Q_{L,0}^* \) and \( \pi_{H,1}^*/\pi_{L,1}^* > \pi_{H,0}^*/\pi_{L,0}^* \) after an inferior entry.

The fact that the \( \theta_H \) is always relatively equal or better off than the \( \theta_L \) when \( \alpha = 1 \) reflects the relative market advantage that \( \theta_H \) enjoys in the PU marketplace. Proposition 2 highlights the key role that PR buyers’ quality sensitivities plays in shaping the competitive equilibrium and relative performance of \( \theta_H \) and \( \theta_L \) in the face of a new entrant. Contrary to our empirical results, we find that \( \theta_H \) is always the same or better off in the face of an entrant relative to \( \theta_L \) when the new buyer’s quality profile mimics the existing buyer pool. Therefore, Proposition 2 establishes that a key component that drives our empirical findings is the positive correlation between entrant type and the quality sensitivity of the new buyers that the new entrants bring.

Our empirical and theoretical setup above has explored the effect of an entrant of much higher or much lower quality than is typical. It is reasonable to inquire – What is the effect of an entrant with intermediate quality (i.e., an entrant quality that falls in the range of quality offered by the PU marketplace)? We use our stylized model to explore this question. When the entrant’s quality is between \( \theta_L \) and \( \theta_H \), their buyers’ quality sensitivities should not be much different from the existing buyers. We hence assume \( \alpha = 1 \) in this case (i.e., \( \alpha \) is the same as that of PU buyers).

**Proposition 3.** Consider a PR entrant of intermediate quality (i.e., \( \theta_L < \theta_E < \theta_H \)), and that PR buyers have the same quality sensitivities as the PU buyers (i.e., \( \alpha = 1 \)). The equilibrium ratio of supply from \( \theta_H \) relative to \( \theta_L \), as well as the equilibrium revenues, are larger after the marquee seller enters. Formally, \( Q_{H,1}^*/Q_{L,1}^* > Q_{H,0}^*/Q_{L,0}^* \) and \( \pi_{H,1}^*/\pi_{L,1}^* > \pi_{H,0}^*/\pi_{L,0}^* \).

Similar to Proposition 2, seller \( \theta_H \)’s quality advantage over seller \( \theta_L \) always makes it better off relative to the latter after the intermediate-quality marquee seller entry. In particular, \( \theta_H \), by means of (relatively) expanding its supply, attracts new PR buyers. This alleviates any losses of its PU buyers to the entrant and further delivers benefits by cannibalizing \( \theta_L \)’s market.

Proposition 3 along with Proposition 2 imply that regardless of the entrant’s quality, high-quality PU sellers will never be worse off than their low-quality peers post PR entry, as long as the demand quality sensitivity distribution does not change (i.e., \( \alpha = 1 \)). In other words, it is not the direct effect
Flexible Supply | Inflexible Supply

Figure 3. Marquee entrants’ effect on (total) PU marketplace revenue.

Note: The shades reflect the change in PU marketplace revenue due to marquee entries. Lighter color indicates larger increases in the revenue. (parametric values: \( \theta_L, \theta_H, \theta_E = \{1.3, 1.35, 1.4\} \)).

of marquee entrants on the platform’s supply (volume and quality), but their indirect effects on the buyers’ quality sensitivities that determines the relative winners and losers in the PU marketplace.

The above analyses assume that the mass of entrant buyers, \( \mu \), takes on a sufficiently large value. In Appendix D.3, we numerically explore our setting when \( \mu \) takes on smaller values and find that for low values of \( \mu \), the effect of marquee entry follows a direction that is similar to Proposition 2: The high-quality PU sellers’ revenues are better off than that of the low-quality PU sellers’, regardless of the entrant’s quality. This occurs as low \( \mu \) implies a smaller localized market expansion effect, and thus the market advantage enjoyed by high-quality PU sellers dominates any localized market expansion effect that may have benefited the low-quality PU seller.

While our analyses in this section so far, with a focus on revenues for high- and low-quality PU sellers, also hint on how the total PU marketplace revenues would fare under a marquee entry, the following analysis takes a closer look. Recall, empirically we had observed that the total PU marketplace revenues had increased under the SPR entrant and decreased under the IPR entrant. To gain further insight, we numerically explore the effect of an entry on PU marketplace revenues.
for an SPR and IPR entrant with a range of $\alpha$ and $\mu$ values. While the insights that follow can be analytically proved, given that the intuition behind them is clear, we present them numerically to be succinct. Figure 3’s first column (which allows sellers to change their supply flexibly) shows that the total PU sellers’ revenues increase with increasing $\alpha$ or $\mu$. A higher value of $\alpha$ implies higher average prices commanded by PU sellers due to entrant (more quality-sensitive) buyers, while a higher value of $\mu$ implies higher total number of buyers, both of which result in higher PU marketplace revenues. Although a higher-quality entrant can ensure a higher value of $\alpha$, it should be noted, however, that one of the effects of a higher-quality entrant is a decrease in PU marketplace revenues due to the entrant steering away quality-sensitive buyers and negatively affecting PU marketplace prices. Thus, entrant quality to achieve higher total PU revenues should be determined in consideration with its direct cannibalizing effect, its indirect expansion effect through entrant buyers (effect of $\alpha$), and the potential size of the entrant buyer pool it brings on-board (effect of $\mu$).

When PU sellers cannot adjust their supply, the effect of the marquee entrant on total PU revenues is analyzed numerically in the second column of Figure 3. Comparing with the first column, it shows that the PU marketplace revenues are higher when sellers can flexibly adjust their supply as compared to when they cannot. This suggests that the platform can play a positive role in enabling supply flexibility to achieve higher total PU seller revenues.

6. Managerial Implications and Conclusion

Growth via inclusion of marquee sellers is a common strategy that is widely used by early-stage online platforms to expand their offerings and accelerate their growth. The implications with regard to the quality of adopted marquee sellers on unbranded sellers in a PU marketplace have not been previously studied and are not well-understood. We bridge this gap in the literature by empirically studying the entry of two marquee sellers of widely different qualities on (unbranded) existing sellers.

This paper makes a few important contributions to the literature. We document the differential effects of entrants (based on their quality) on PU marketplace sellers. Specifically, we find that while high-quality PU sellers expand their supply share relative to low-quality PU sellers when a superior-quality entrant joins, low-quality PU sellers disproportionately expand their supply relative to high-quality PU sellers when an inferior quality entrant joins. This asymmetric supply response results in an asymmetric shift in typical seller quality within the PU marketplace based on the entrant’s type: PU marketplace quality shifts in the direction of the entrant. This externality is broken down into crucial mechanisms using empirical analyses and a stylized theoretical model. We highlight the contradicting influences of the market expansion and market stealing effects brought
about by an entrant. We further delineate the role of existing sellers’ supply flexibility and the quality sensitivity of buyers brought to the platform due to the entrant in moderating the entrant’s competition effects.

One of the key implications of our findings for managers engaging in marketplace expansion through marquee entrants is its externality on unbranded seller quality. Failing to incorporate this indirect effect, a marketplace may set itself on an unanticipated cycle of growth skewed toward one end of the quality spectrum. A platform focused on maintaining a high-quality reputation for its public marketplace over the long-term might therefore want to steer away from inviting low-quality brands to the platform. On the other hand, a platform focused on growing revenues for its public marketplace should seek to invite entrants with the potential to attract a large mass of buyers, ideally who are also quality sensitive.

We note that our analyses and recommendations are geared towards marketplaces at early-stages of growth – such that each marquee seller’s entry can noticeably alter the platform’s landscape. At a mature stage of growth, the dynamics of marquee entry might differ; the marginal effect of marquee entry on a public marketplace would likely be limited in size.

The importance and prevalence of marquee seller adoption by platforms and its relatively nascent academic understanding makes this an exciting area for research in the coming years. A few opportunities for future research arise when we consider the limitations of this study. First, sellers on our platform were allowed to (almost instantaneously) change their supply quantities, which is consistent with many gig economy and other contemporary marketplaces. However, several other marketplaces do not share this flexibility. While our theoretical model speaks to this (supply inflexibility) setting, future empirical examination of such settings would be of interest. Second, further empirical investigation of the dependence of quality sensitivity of new buyers and their linkages to the entrant quality, a phenomenon that drives our findings, would enrich our understanding of platforms and mechanisms that are effective at creating cycles of growth. Third, the notion of quality that we use in this study is informational quality. We control for product quality and also find that our measure of quality - dispute rates - is independent of product quality. Our setting only allows sellers to be separated by informational quality (dispute rates). Future research may study the effect of marquee entrant quality where sellers are separable by their product quality offerings. While we do not have reasons to expect the main findings to differ in substance, a validation or a rejection of this extrapolation would be an important contribution. Fourth, we study the short-term effects of marquee entry in this paper. The short-term implications should be substantially correlated with long-term outcomes in our context, as is often the case in other online platforms contexts (Dinerstein et al. 2018). However, explicitly studying the long-term implications both theoretically and empirically will make for an interesting future study. Finally,
the effect of marquee entry on the PU marketplace is only a piece of a puzzle, albeit an important one. Studying the effects of marquee entry on other aspects of the platform ecosystem (e.g., overall platform quality and revenues) will help build a comprehensive understanding of this important research stream.

References


Glaeser, Chloe Kim, Ken Moon, Xuanming Su. 2020. Pick-up, delivery, or both? an online grocer’s optimal fulfillment models.


Yu, Qiuping, Yiming Zhang, Yong-Pin Zhou. 2020. Delay information in virtual queues: A large-scale field experiment on a ride-sharing platform. Available at SSRN 3687302.

Appendix A: Robustness Checks

A.1. Robustness Checks for the Effect of Marquee Entry on PU Sellers’ Supply and Revenues

A.1.1. Alternative Quality Variables. We investigate whether entrants’ average and heterogeneous effects on PU sellers’ supply and revenues are robust to two different PU sellers’ quality specifications. First, we compare the effects between PU sellers with dispute rates lower than the 25\textsuperscript{th} -percentile and the rest by using the dummy variable $TopQuality_i$, to indicate the quality type. Second, we use PU sellers’ dispute rates (logged), denoted by $DisputeRate_i$, to represent their quality.\footnote{We consider log scale to reduce the variable’s skewness.} For both entries, we re-estimate Regression (1) by replacing $HighQuality_i$ with the quality type variable specified above.

The estimation results under $TopQuality$ are displayed in Table 8. Entrants’ heterogeneous effects on PU sellers’ supply and revenues are consistent with the heterogeneous effects revealed in Table 4. The estimation results under $DisputeRate$ are displayed in Table 9 and are mostly consistent with the heterogeneous effects shown in Table 4. As shown in Table 9’s columns (1) and (3), PU sellers with high dispute rates increase their revenues and supply significantly less than do those with low-quality dispute rates under the superior entry, which is consistent with the findings shown in Table 4. Under the inferior entry, Table 9’s columns (1) and (5) show that PU sellers with high dispute rates decrease their revenues and supply less than those with low-quality dispute rates, which is consistent with Table 4. In sum, this suggests that both entrants’ heterogeneous effects on PU sellers’ supply and revenues are robust to alternate quality specifications.

<table>
<thead>
<tr>
<th></th>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Revenue</td>
<td>(4) Revenue</td>
</tr>
<tr>
<td></td>
<td>(2) Log(Price)</td>
<td>(5) Log(Price)</td>
</tr>
<tr>
<td></td>
<td>(3) # Listings</td>
<td>(6) # Listings</td>
</tr>
<tr>
<td>$Trt \times Post \times TopQuality$</td>
<td><strong>3.602</strong>$^{***}$</td>
<td><strong>1.101</strong>$^{**}$</td>
</tr>
<tr>
<td></td>
<td>(1.168)</td>
<td>(0.556)</td>
</tr>
<tr>
<td>$Trt \times Post$</td>
<td>0.280</td>
<td>−0.219</td>
</tr>
<tr>
<td></td>
<td>(0.575)</td>
<td>(0.252)</td>
</tr>
<tr>
<td>$Trt \times TopQuality$</td>
<td>−1.458$^*$</td>
<td>−0.604</td>
</tr>
<tr>
<td></td>
<td>(0.846)</td>
<td>(0.476)</td>
</tr>
<tr>
<td>$Post \times TopQuality$</td>
<td>−3.837$^{***}$</td>
<td>−0.046</td>
</tr>
<tr>
<td></td>
<td>(1.080)</td>
<td>(0.467)</td>
</tr>
<tr>
<td>PU Sellers’ Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Month Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>502</td>
<td>220</td>
</tr>
<tr>
<td>Adjusted R(^2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>−537.244</td>
<td>−818.243</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8. Entrants’ heterogeneous effects using 25\textsuperscript{th}-percentile dispute rates as the high-quality threshold.
Title: Marketplace Expansion through Marquee Seller Adoption

<table>
<thead>
<tr>
<th></th>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Revenue</td>
<td>(2) Log(Price)</td>
</tr>
<tr>
<td></td>
<td>(4) Revenue</td>
<td>(5) Log(Price)</td>
</tr>
<tr>
<td>$\text{Trt} \times \text{Post} \times \text{DisputeRate}$</td>
<td>$-18.385^{***}$</td>
<td>$-7.045^{***}$</td>
</tr>
<tr>
<td></td>
<td>(7.020)</td>
<td>(2.317)</td>
</tr>
<tr>
<td>$\text{Trt} \times \text{Post}$</td>
<td>$3.501^{***}$</td>
<td>$1.238^{***}$</td>
</tr>
<tr>
<td></td>
<td>(1.025)</td>
<td>(0.431)</td>
</tr>
<tr>
<td>$\text{Trt} \times \text{DisputeRate}$</td>
<td>$9.340^{**}$</td>
<td>$3.360^*$</td>
</tr>
<tr>
<td></td>
<td>(4.052)</td>
<td>(1.868)</td>
</tr>
<tr>
<td>$\text{Post} \times \text{DisputeRate}$</td>
<td>$16.985^{**}$</td>
<td>$3.076$</td>
</tr>
<tr>
<td></td>
<td>(6.677)</td>
<td>(2.185)</td>
</tr>
</tbody>
</table>

PU Sellers’ Fixed Effects | Y | Y | Y | Y | Y | Y |
Month Fixed Effects       | Y | Y | Y | Y | Y | Y |
Observations              | 502 | 220 | 502 | 2.281 | 645 | 2.281 |
Adjusted $R^2$            | 0.475 | 0.650 |
Log Likelihood            | $-539.824$ | $-817.556$ | $-2,097.806$ | $-2,499.822$

Note: $^* p<0.1$; $^{**} p<0.05$; $^{***} p<0.01$

Table 9. Entrants’ heterogeneous effects using PU sellers’ dispute rates to indicate their types.

A.1.2. Alternative Control Group. In this analysis, we show that the heterogeneous effects presented in Table 4 are robust to alternative control groups. In the PU marketplace, we select the listings of the unclassified category, which represents auctions of mixed products from multiple categories, as the alternative control group under both the superior and the inferior entries. Note that no PR marketplace has listings within the unclassified category, and their buyers are largely uninterested in the category. Hence, PR marketplaces’ effect on PU marketplace’s unclassified listings is limited. That said, we did not employ the unclassified category as the control category in the main analysis due to its potential supply overlap with the treated category – that is, some listings of unclassified category listings contain consumer electronics and appliances.

We re-estimate Regression (1) using this alternative control group and show the results in Table 10. As is evident in the table, both entries’ heterogeneous effects on PU sellers’ listings and revenues are consistent with those in Table 4: High-quality (low-quality) PU sellers have a relative boost in their revenues and supply quantities after the superior (inferior) entry. This suggests that our findings regarding marquee entrants’ heterogeneous effects on PU sellers are robust to the choice of the control group.

A.1.3. No Seasonality Control. The entrants’ heterogeneous effects mostly hold when we no longer restrict analysis time windows so as to account for seasonality. Instead of selecting pre- and post-entry periods so that they cover the same months of a year, we let the entry date be the end date of the pre-entry period and the start date of the post-entry period. For the superior entry, the pre-entry period starts in April 2012 and ends in March 2013, and the post-entry period starts in March 2013 and ends in November 2013. For the inferior entry, the pre-entry period starts in January 2015 and ends in July 2015, and the post-entry period starts in July 2015 and ends in May 2016. We re-estimate Regression (1) using the extended samples, and the resulting estimates for each entry are presented in Table 11. In particular, column (3) of the
Table 10. Entrants’ heterogeneous effects using the unclassified category as a control.

<table>
<thead>
<tr>
<th></th>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Revenue</td>
<td>(4) Revenue</td>
</tr>
<tr>
<td>Trt × Post × HighQuality</td>
<td>3.887**</td>
<td>-0.551*</td>
</tr>
<tr>
<td></td>
<td>(1.937)</td>
<td>(0.295)</td>
</tr>
<tr>
<td>Trt × Post</td>
<td>-2.198</td>
<td>0.406*</td>
</tr>
<tr>
<td></td>
<td>(1.855)</td>
<td>(0.244)</td>
</tr>
<tr>
<td>Trt × HighQuality</td>
<td>-1.385</td>
<td>0.374</td>
</tr>
<tr>
<td></td>
<td>(1.524)</td>
<td>(0.239)</td>
</tr>
<tr>
<td>Post × HighQuality</td>
<td>-2.667</td>
<td>0.677**</td>
</tr>
<tr>
<td></td>
<td>(1.898)</td>
<td>(0.269)</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

A.1.4. Effect of Marquee Entry on PU Sellers’ Listing Compositions. We examine whether PU sellers significantly change their listing composition – lot size and retail value per item – in each of their post-entry listings. To detect any change in PU sellers’ listing compositions, we look at the entry effect on the average number of items per listing each month and the average retail value per listed product each seller × category × month. An increase (decrease) in the average retail value per product indicates that PU sellers include more (less) valuable items in their listings. For PU seller \( i \) in category \( k \) with listings in month \( t \), we denote the average number of items per listing and the average retail value per product, both in log scale, by \( L_{i,k,t} \), \( \beta_{3(10)} \) and \( \gamma_{3(10)} \) in the following linear regressions to capture the effects we are examining:

\[
L_{i,k,t} = \beta_{0(10)} + \gamma_{0(10)} \text{HighQuality}_i + (\beta_{1(10)} + \gamma_{1(10)} \text{HighQuality}_i) \times \text{Trt}_k \\
+ (\beta_{2(10)} + \gamma_{2(10)} \text{HighQuality}_i) \times \text{Post}_t \\
+ (\beta_{3(10)} + \gamma_{3(10)} \text{HighQuality}_i) \times \text{Trt}_k \times \text{Post}_t + \eta_{i(10)} + \zeta_{t(10)} + \epsilon_{i,k,t}. \tag{10}
\]

Tables 12 presents the estimates under the superior and inferior entries. We find that low-quality PU sellers do not change, in a statistically significant manner, their listing lot sizes or compositions after the marquee entries in a statistically significant manner. Also, changes in high-quality PU sellers’ listing lot sizes and compositions are not statistically different than those of low-quality PU sellers.
### Table 11. Entrants’ heterogeneous effects without controlling for seasonality.

<table>
<thead>
<tr>
<th></th>
<th>Superior Entry</th>
<th></th>
<th>Inferior Entry</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Revenue</td>
<td>(2) Price</td>
<td>(3) # Listings</td>
<td>(4) Revenue</td>
</tr>
<tr>
<td>Trt × Post × HighQuality</td>
<td>0.662 (0.846)</td>
<td>0.921** (0.378)</td>
<td>1.141* (0.685)</td>
<td>−1.688*** (0.385)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>−0.492 (0.267)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>−1.472*** (0.373)</td>
</tr>
<tr>
<td>Trt × Post</td>
<td>0.704 (0.677)</td>
<td>−0.619** (0.282)</td>
<td>0.745 (0.492)</td>
<td>0.274 (0.324)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.343 (0.218)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>−0.003 (0.304)</td>
</tr>
<tr>
<td>Trt × HighQuality</td>
<td>−1.234** (0.558)</td>
<td>−0.210 (0.285)</td>
<td>−1.168** (0.519)</td>
<td>0.917*** (0.332)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.443 (0.238)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.290*** (0.331)</td>
</tr>
<tr>
<td>Post × HighQuality</td>
<td>−0.468 (0.752)</td>
<td>−0.371 (0.322)</td>
<td>0.084 (0.601)</td>
<td>1.609*** (0.360)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.561** (0.248)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.349*** (0.349)</td>
</tr>
</tbody>
</table>

PU Sellers’ Fixed Effects: Y Y Y Y Y Y
Month Fixed Effects: Y Y Y Y Y Y
Observations: 605 268 605 3,803 1,097 3,803
Adjusted R²: 0.390 0.608 0.680
Log Likelihood: −678.794 −1,013.272 −1,369.784 −4,390.500

Note: *p<0.1; **p<0.05; ***p<0.01

### Table 12. Entree’s effects on PU sellers’ listing lot sizes and compositions.

<table>
<thead>
<tr>
<th></th>
<th>Superior Entry</th>
<th></th>
<th>Inferior Entry</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Avg. Lot Size</td>
<td>(2) Avg. Retail Value</td>
<td>(3) Avg. Lot Size</td>
<td>(4) Avg. Retail Value</td>
</tr>
<tr>
<td>Trt × Post</td>
<td>0.575 (1.017)</td>
<td>−0.841 (0.824)</td>
<td>0.466 (0.611)</td>
<td>−0.665 (0.497)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trt × Post × HighQuality</td>
<td>−1.400 (1.136)</td>
<td>1.350 (0.900)</td>
<td>−0.757 (0.648)</td>
<td>0.698 (0.540)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PU Sellers’ Fixed Effects: Y Y Y Y</td>
<td>Y Y</td>
<td>Y Y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Month Fixed Effects: Y Y Y Y</td>
<td>Y Y</td>
<td>Y Y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations: 146 141 402 387</td>
<td>402 387</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R²: 0.476 0.658</td>
<td>0.711 0.807</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

**A.1.5. Effect of Marquee Entry on PU Sellers’ Entry-Exit Numbers.** We examine whether marquee entries significantly impact the number of PU sellers’ entering and exiting the PU marketplace. PU sellers’ entry and exit times can be inferred by the dates of their first and last listings, respectively. $N_{k,\theta,t}$ denotes the number of entering or exiting PU sellers of category $k$ with quality $\theta$ in month $t$. For the analysis period of SPR entry, we focus on PU sellers who specialize in the consumer electronics or the jewelry and toys categories. For the IPR entry period, we focus on PU sellers who specialize in consumer electronics or appliances. $Trt_k$ indicates whether category $k$ belongs to the treatment category, $HighQuality\theta$ indicates whether or not $\theta$ denotes the high-quality type, and $Post_t$ indicates whether month $t$ comes after the marquee entry. We estimate the following regression to identify any marquee entrants’ effects on PU sellers’ entries.
and exits numbers:

$$\log(N_{k,\theta,t}) = \beta_0^{(11)} + \gamma_0^{(11)} HighQuality_{\theta} \left( \beta_1^{(11)} + \gamma_1^{(11)} HighQuality_{\theta} \right) \times Trt_k$$

$$+ \left( \beta_2^{(11)} + \gamma_2^{(11)} HighQuality_{\theta} \right) \times Post_t + \left( \beta_3^{(11)} + \gamma_3^{(11)} HighQuality_{\theta} \right) \times Trt_k \times Post_t + \epsilon_{i,k,t} \right).$$

The estimates of Regression (11) are displayed in Table 13. As shown in the table, neither PU sellers’ entries nor their exits are affected by marquee entries in a statistically significant manner.

<table>
<thead>
<tr>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) PU Entry</td>
<td>(2) PU Exit</td>
</tr>
<tr>
<td>Trt $\times$ Post $\times$ HighQuality</td>
<td>0.620</td>
</tr>
<tr>
<td></td>
<td>(0.444)</td>
</tr>
<tr>
<td>(3) PU Entry</td>
<td>(4) PU Exit</td>
</tr>
<tr>
<td>Trt $\times$ Post $\times$ HighQuality</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(0.408)</td>
</tr>
<tr>
<td>Observations</td>
<td>76</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.368</td>
</tr>
</tbody>
</table>

*Note:* $^* p < 0.1; ^{**} p < 0.05; ^{***} p < 0.01$

Table 13. Entrants’ effects on PU sellers’ monthly entries and exits.

A.2. Robustness Checks for Localized Market Stealing Effect

A.2.1. Alternative Buyer-Level Control Variables. We examine the effectiveness of buyers’ pre-entry monthly participation levels to control for buyer specific unobservables by re-estimating Regression (2) with buyers’ fixed effects substituted by buyers’ pre-entry monthly participation. The estimates are shown in Table 14. It is notable that the PU buyers’ participation changes identified by this alternative specification are consistent with Table 5. This analysis suggests that buyers’ pre-entry monthly participation is sufficient to capture buyers’ specific idiosyncrasies. This helps justify Regression (3)’s specification, where we use buyers’ pre-entry monthly participation to control for their idiosyncrasies, as we cannot use buyer fixed effects there.

<table>
<thead>
<tr>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td>ParticipatePU</td>
<td></td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Post $\times$ PctHighQualityParticipated</td>
<td>$-0.647^{**}$</td>
</tr>
<tr>
<td></td>
<td>(0.328)</td>
</tr>
<tr>
<td>Control for Product-related Effects</td>
<td>Y</td>
</tr>
<tr>
<td>Control for Buyers’ Participation</td>
<td>Y</td>
</tr>
<tr>
<td>Control for Buyers’ Experiences</td>
<td>Y</td>
</tr>
<tr>
<td>Month Fixed Effects</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>13,780</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>$-6,503.760$</td>
</tr>
</tbody>
</table>

*Note:* $^* p < 0.1; ^{**} p < 0.05; ^{***} p < 0.01$

Table 14. PU buyers’ participation levels in PU sellers’ listings.
A.2.2. Alternative Buyer Type Classification. We examine whether the identified localized market stealing is robust to alternative buyer quality preference definitions. Here, we classify buyers based on the primary quality types of listings they participate in – $HighTypeBuyer_j$, which is defined as

$$HighTypeBuyer_j = 1\{PctHighQualityParticipated_j > 0.5\}.$$ 

We substitute $PctHighQualityParticipated_j$ in Regressions (2) and (3) with $HighTypeBuyer_j$. The revised estimates are presented in Table 15. As shown in the table, the estimates are consistent with Table 5. This suggests that the identified localized market stealing is robust to the alternative buyer type classification.

<table>
<thead>
<tr>
<th></th>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) PU</td>
<td>(2) PR</td>
</tr>
<tr>
<td>$Post \times HighTypeBuyer$</td>
<td>$-0.735^{***}$</td>
<td>$0.485^{***}$</td>
</tr>
<tr>
<td></td>
<td>$(0.216)$</td>
<td>$(0.072)$</td>
</tr>
<tr>
<td>$HighTypeBuyer$</td>
<td>$1.738^{***}$</td>
<td>$-0.562^{***}$</td>
</tr>
<tr>
<td></td>
<td>$(0.486)$</td>
<td>$(0.112)$</td>
</tr>
<tr>
<td>Control for Product-related Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Control for Buyers’ Experiences</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Control for Buyers’ Participation</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Buyer Fixed Effects</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Month Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>13,780</td>
<td>7,638</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>$-5,201.413$</td>
<td>$-1,220.131$</td>
</tr>
</tbody>
</table>

Table 15. PU buyers’ participation in PU and PR listings using discrete buyer types.

Note: By PU we denote ParticipatePU and by PR we denote ParticipatePR.

A.3. Robustness Checks for Localized Market Expansion Effect

A.3.1. PR Buyers’ Choice of PU sellers. As a robustness check to Regression (4), we model PR buyers’ choice of an individual seller $i$ instead of any seller of high or low quality. Indicator $ChoosePU_{i,j}$ denotes whether PR buyer $j$ chooses to place a bid on any listing of PU seller $i$ throughout buyer $j$’s entire lifetime. As the simulated examples in Appendix B.6 suggest, it is crucial to control for product-related influences in buyers’ choices when identifying their sensitivity differences. Therefore, we only focus on a subsample of data here (i.e., iPhones). Buyers’ choices also depend on various seller characteristics, including their quality. Then, variable $HighQuality_i$ captures buyers’ preferences for high-quality PU sellers. We also control for PU sellers’ other characteristics, such as number of completed transactions and number of repeat buyers, which are denoted by vector $X_i^{(12)}$. Lastly, buyers’ seller choices depend on the overall market condition while they are active (e.g., number of listings and available products). In contrast to Regressions (4) and (5), where the market condition only needs to be controlled for during a given month or during a given auction, this analysis requires the market condition experienced by each buyer throughout their lifetime, ranging from a few days to a few months, to be controlled for. We also note that each buyer’s
market experience is unique and specific to when and how long they are active. Therefore, we use buyers’
fixed effects ($\nu_j$) to control for these market-level influences. The regression specification is:

$$\text{logit}[\Pr(\text{ChoosePU}_{i,j} = 1)] = \beta_0^{(12)} + \beta_1^{(12)} \text{HighQuality}_i + \beta_2^{(12)} \text{T}_2 X_{i}^{(12)} + \nu_j. \quad (12)$$

Table 16, presents the estimates of Regression (12). We see that the estimates are consistent with those
in Table 6 in the paper, suggesting the identified effect is robust to alternative specifications.

<table>
<thead>
<tr>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ChoosePU</strong></td>
<td></td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$\text{HighQuality}$</td>
<td>0.490***</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
</tr>
<tr>
<td>Control for PU sellers’ Characteristics</td>
<td>Y</td>
</tr>
<tr>
<td>Buyer Fixed Effects</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>4,822</td>
</tr>
</tbody>
</table>

*Note: *p<0.1; **p<0.05; ***p<0.01

Table 16. The localized market expansion estimated based on PR buyers’ choices between PU sellers.

**A.3.2. Buyers’ Quality Sensitivity Comparison with Alternative Quality Specifications.** We
investigate whether the difference between buyers’ sensitivities identified by Regression (5) is robust to
alternative quality specifications. As we did in Appendix A.1.1, we check robustness with two different PU
sellers’ quality specifications: $\text{TopQuality}_i$ and $\text{DisputeRate}_i$. As defined earlier, $\text{TopQuality}_i$ is 1 for PU
sellers with dispute rates lower than the 25<sup>th</sup>-percentile and 0 otherwise. $\text{DisputeRate}_i$ is logged PU sellers’
dispute rates. The estimation results under $\text{TopQuality}_i$ and $\text{DisputeRate}_i$ replacements are displayed in
Tables 17 and 18, respectively. We find that the effects are mostly consistent with those identified earlier,
though one estimate is not statistically significant (p-value = 0.29). These checks suggest that the buyer
sensitivity analysis is robust to alternative quality specifications.

**A.3.3. Buyers’ Quality Sensitivity Comparison via Choices between PU sellers.** We test the
robustness of buyers’ quality sensitivity differences by comparing their choices between PU sellers. We follow
almost the same settings as in Appendix A.3.1, except that the sample contains the choice of both PR and
PU sellers. We let $\text{Is}_{\text{PR buyer}}_j$ indicate whether buyer $j$ is a PR buyer or not. Then, we consider the
cross-term $\text{Is}_{\text{PR buyer}}_j \times \text{HighQuality}_i$ to tease out preference differences between PR and PU buyers
over high-quality PU sellers. In addition, we control for buyers’ heterogeneous preferences over sellers’ other
characteristics (i.e., $\text{Is}_{\text{PR buyer}}_j \times X_i$). Therefore, the regression for comparing buyers’ quality sensitivities
through their PU seller choices is specified below:

$$\text{logit }[\Pr(\text{ChoosePU}_{i,j} = 1)] = \beta_0^{(13)} + \gamma_0^{(13)} \text{Is}_{\text{PR buyer}}_j + (\beta_1^{(13)} + \gamma_1^{(13)} \text{Is}_{\text{PR buyer}}_j) \times \text{HighQuality}_i + (\beta_2^{(13)} + \gamma_2^{(13)} \text{Is}_{\text{PR buyer}}_j)^T \times X_{i}^{(13)} + \nu_j. \quad (13)$$
### Table 17. Quality sensitivity comparison between PR buyers and PU buyers estimated using 25th-percentile dispute rates as the high-quality threshold.

<table>
<thead>
<tr>
<th></th>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bid</td>
<td></td>
</tr>
<tr>
<td>$Is_{PRbuyer} \times TopQuality$</td>
<td>0.089*** (0.029)</td>
<td>-0.062* (0.033)</td>
</tr>
<tr>
<td>Buyers’ Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Characteristics of Listings</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>PU Sellers’ Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Month Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>980</td>
<td>1,624</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.723</td>
<td>0.784</td>
</tr>
</tbody>
</table>

*Note:* *p<0.1; **p<0.05; ***p<0.01

### Table 18. Quality sensitivity comparison between PR buyers and PU buyers estimated using dispute rates to denote their types.

<table>
<thead>
<tr>
<th></th>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bid</td>
<td></td>
</tr>
<tr>
<td>$Is_{PRbuyer} \times DisputeRate$</td>
<td>-0.170 (0.164)</td>
<td>0.314* (0.135)</td>
</tr>
<tr>
<td>Buyers’ Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Characteristics of Listings</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>PU Sellers’ Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Month Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>980</td>
<td>1,624</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.715</td>
<td>0.790</td>
</tr>
</tbody>
</table>

*Note:* *p<0.1; **p<0.05; ***p<0.01

The estimates of Regression (13) are presented in Table 19, where we find consistent estimates with our main analysis in the paper. This suggests that the identified effect that PR buyers under the superior (inferior) entry are more (less) sensitive to quality than are the PU buyers is robust to some alternative specifications.


We examine if the quality sensitivities of PU buyers change around the time of marquee entries. If so, the effect of this should be recognized, in addition to the localized market stealing and expansion effects we have identified. To study this, we compare the quality sensitivity of PU buyers who registered before a marquee entry with those who registered after. $PostPUBuyer_j$ is 1 if a PU buyer $j$ registered post-entry. We replace $Is_{PRbuyer}$ with $PostPUBuyer_j$ in Regression (5) and re-use the same data setup except that we now apply the regression model to PU buyers only. The coefficient of $PostPUBuyer_j \times HighQuality_{i,t}$, which captures the quality sensitivity shift within PU buyers, is estimated in Table 20. As is evident in the table, no statistically significant quantity sensitivity change occurs around the time of either of the entries.
Table 19. Quality sensitivity comparison between PR buyers and PU buyers estimated based on buyers’ choice between PU sellers.

Table 20. Quality sensitivity comparison between PU buyers: Pre-entry registered vs. post-entry registered.

Appendix B: Supporting Empirical Evidence

B.1. Stability of PU Sellers’ Quality

Similar to the empirical setting specified in Section 4.1, we adopt a difference-in-differences approach to examine whether the SPR and IPR entries significantly affect individual PU sellers’ quality. PU sellers of consumer electronics are considered as the treatment group. The control group under the SPR entry are PU sellers of jewelry and toy listings, and the control group under the IPR entry are PU sellers of appliances listings. Observations are collected at a seller-month level. We let $Quality_{i,t}$ denote seller $i$’s quality variable in month $t$, which is the dependent variable. Separately, we let the indicator of whether seller $i$ has high quality (i.e., $HighQuality_{i,t}$) and its logged dispute rate measure $Quality_{i,t}$. Then, we let $Trt_i$ and $Post_t$ indicate the treatment group and the post-entry period, respectively. In addition, we incorporate PU sellers’ fixed effects ($\eta_i$) to control for sellers’ idiosyncratic characteristics (i.e., capacity) and month fixed effects.
(ζ_t) to control for unobserved market-level shocks. Therefore, the regression model is specified as:

\[ \text{Quality}_{i,t} = f \left( \beta_0^{(14)} + \beta_1^{(14)} \text{Trt}_i + \beta_2^{(14)} \text{Post}_t + \beta_3^{(14)} \text{Trt}_i \times \text{Post}_t + \eta_i + \zeta_t \right), \quad (14) \]

where \( f \) stands for the logistic link function if the dependent variable is the high-quality indicator, and it stands for the linear regression if the dependent variable is the dispute rate. In Regression (14), coefficient \( \beta_3^{(14)} \) captures the marquee entrants’ potential impacts on PU sellers’ quality. The estimated results are shown in Table 21. As is evident in the table, both marquee entries have no statistically significant effect on individual PU sellers’ quality. In other words, PU sellers rarely adjust their quality in response to marquee entries. Therefore, we consider quality as a PU seller attribute and not a decision lever for the time period of our analysis.

<table>
<thead>
<tr>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Quality Type</td>
<td>(2) Dispute Rate</td>
</tr>
<tr>
<td>Trt × Post</td>
<td>1.282</td>
</tr>
<tr>
<td>(1.313)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>PU Sellers’ Fixed Effects</td>
<td>Y</td>
</tr>
<tr>
<td>Month Fixed Effects</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>502</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.836</td>
</tr>
</tbody>
</table>
| Log Likelihood | -79.028 | -207.153 | *p<0.1; **p<0.05; ***p<0.01

Table 21. Marquee entries’ effects on individual PU sellers’ quality.

B.2. Correlation Examination of Dispute Rate with Product Type and Condition among Consumer Electronics Listings

We implement logistic regression to examine the correlation between the dispute rates on the one hand and product types and conditions on the other hand. The regression is performed at the listing level. We regress each listing’s dummy variable of being disputed or not on their product type and their quality level, respectively. First, the left panel of Table 22 presents the estimates of disputes’ correlation with the product category. As evident in the table, no significant correlation is identified. Second, we examine the correlation between the dispute rate and the quality level. Since sellers tend to use different labels to describe their products’ condition, we categorize the labels broadly as high-quality (e.g., new, new-open box, shelf pulls) and low-quality (e.g., customer returns, open box returns, refurbished, used). Then, the right panel of Table 22 compares the correlation between the dispute rate and the quality level. As shown in the table, there is little correlation between the dispute rate and the product quality.

B.3. Diversity of PU Sellers’ Product Condition Spectrum

Each of the PU sellers’ listings fall under one of the following condition labels: new, shelf pulls, new-open box, refurbished, customer returns, open box returns, used, and salvage. We let \( C \) denote the set of condition labels. Most PU sellers list products under more than one condition label. Hence, we use the Gini index
<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Dispute Dummy Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cell Phones</td>
<td>12.003 (309.120)</td>
</tr>
<tr>
<td>Computer Accessories</td>
<td>13.055 (309.120)</td>
</tr>
<tr>
<td>Computers</td>
<td>10.963 (309.121)</td>
</tr>
<tr>
<td>Computers and Software</td>
<td>12.024 (309.120)</td>
</tr>
<tr>
<td>Consumer Electronics</td>
<td>11.804 (309.120)</td>
</tr>
<tr>
<td>Digital Cameras</td>
<td>-0.00000 (336.855)</td>
</tr>
<tr>
<td>Digital Picture Accessories</td>
<td>-0.00000 (618.240)</td>
</tr>
<tr>
<td>GPS</td>
<td>11.774 (309.122)</td>
</tr>
<tr>
<td>iPods</td>
<td>-0.00000 (437.161)</td>
</tr>
<tr>
<td>Phones</td>
<td>13.566 (309.123)</td>
</tr>
<tr>
<td>Printers</td>
<td>9.759 (309.121)</td>
</tr>
<tr>
<td>Software</td>
<td>-0.00000 (618.240)</td>
</tr>
<tr>
<td>Video Games</td>
<td>13.161 (309.121)</td>
</tr>
<tr>
<td>Constant</td>
<td>-13.566 (309.120)</td>
</tr>
</tbody>
</table>

Observations 32,486
Log Likelihood -14,186.180

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Dispute Dummy Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low-quality</td>
<td>0.033 (0.034)</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.685*** (0.029)</td>
</tr>
</tbody>
</table>

Observations 31,944
Log Likelihood -14,024.360

Note: *p<0.1; **p<0.05; ***p<0.01

Table 22. Correlation between dispute tendency and product category (left); Correlation between dispute tendency and product quality (right).

... to measure the heterogeneity of a given PU seller’s product conditions. In particular, the Gini index of PU seller $i$ is calculated as follows:

$$g_i = 1 - \sum_{c \in C} p_{i,c}^2,$$

where $p_{i,c}$ is the percentage of the seller’s listings under category $c$. In Figure 4, we present the distribution of PU sellers’ product condition Gini indices. As is evident in the plot, product conditions are quite diversified for most PU sellers. In particular, only 4% of PU sellers only list products under one condition label.

B.4. Parallel Trends for Difference-in-Differences Analysis

To formally verify the parallel assumption suggested by Figure 2, we follow Autor (2003) by regressing PU sellers’ monthly listings on the treatment group indicator, the monthly dummy variables, and the cross-term between the two, which gauge the trend differences between the treatment and the control groups, using negative binomial regression. We also control for sellers’ fixed effects. Then, the parallel between pre-trends necessitate that the coefficients of the cross-term for the pre-treatment months are insignificant. Figure...
Figure 4. Distribution of PU sellers’ Gini indices regarding product condition.

Figure 5. Trend comparison of PU sellers’ monthly listings between the treatment group and the control group under the superior (left) and inferior (right) entry.

Note: Vertical bands represent $\pm 1.96$ times the standard error of each point estimate. The two vertical dashed lines specify the periods before and after the entry.

5 displays the estimates of the interaction terms for the superior and inferior entries. The vertical bands represent each coefficient’s 95% confidence interval. As is evident in the figure, all pre-treatment cross-term coefficients are not significantly different from 0. In other words, the parallel assumption holds between the treatment and the control groups.
To further establish the parallel of pre-trend among PU sellers from different groups and with different qualities, Autor (2003)'s approach becomes ineffective for our sample. Due to the small sample size, especially under the superior entry (see Table 4), relative to the number of coefficients to estimate, including the cross-term among the treatment group indicator, monthly dummies, and the high-quality indicator, the coefficients cannot be estimated efficiently. To remedy this issue, we use a “pseudo-treatment” approach. In particular, we introduce a pseudo treatment at the midpoint of the pre-treatment period under both the entries. PostPseudo indicates if a month t comes after the pseudo treatment. We modify Regression (1) by replacing Post with PostPseudo and apply it to pre-treatment period observations only. Any trend differences between the treatment group and the control group would be captured by the coefficient of $Trt_k \times PostPseudo_t$, and any trend differences between PU sellers of different quality types would be captured by the coefficient of $Trt_k \times PostPseudo_t \times HighQuality_{i,t}$.

The estimation results are presented in Table 23. The coefficients for $Trt_k \times PostPseudo_t$ under both entries are not statistically significant, which suggests that the trends between the treatment group and the control group prior to marquee entry are parallel. Moreover, the coefficients of $Trt_k \times PostPseudo_t \times HighQuality$ under both entries are also not statistically significant. This gives validity to the parallel trends assumption between the high-quality and low-quality PU sellers.

<table>
<thead>
<tr>
<th>Superior Entry</th>
<th>Inferior Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Revenue</td>
<td>(4) Revenue</td>
</tr>
<tr>
<td>(2) Price</td>
<td>(5) Price</td>
</tr>
<tr>
<td>(3) # Listings</td>
<td>(6) # Listings</td>
</tr>
<tr>
<td>$Trt \times PostPseudo$</td>
<td>$Trt \times PostPseudo$</td>
</tr>
<tr>
<td>−0.887 (0.807)</td>
<td>−0.704 (0.452)</td>
</tr>
<tr>
<td>−0.019 (0.040)</td>
<td>−0.013 (0.030)</td>
</tr>
<tr>
<td>0.330 (0.596)</td>
<td>−0.475 (0.389)</td>
</tr>
<tr>
<td>$Trt \times PostPseudo \times HighQuality$</td>
<td>$Trt \times PostPseudo \times HighQuality$</td>
</tr>
<tr>
<td>1.036 (1.060)</td>
<td>0.346 (0.531)</td>
</tr>
<tr>
<td>0.040 (0.057)</td>
<td>0.004 (0.035)</td>
</tr>
<tr>
<td>−0.276 (0.845)</td>
<td>0.142 (0.469)</td>
</tr>
<tr>
<td>PU Sellers’ Fixed Effects</td>
<td>PU Sellers’ Fixed Effects</td>
</tr>
<tr>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Month Fixed Effects</td>
<td>Month Fixed Effects</td>
</tr>
<tr>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>261</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.531</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>−322.538</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Table 23. Parallel trend checks regarding PU sellers’ monthly listings using pseudo treatment.

B.5. Average Effects of SPR and IPR Entries

We implement the difference-in-differences method to estimate the SPR and IPR entries’ average effects on PU sellers’ revenues, the average price per listing, and the number of monthly listings, without differentiating sellers’ quality types. The model specification is almost the same as Regression (1) except that variable HighQuality is discarded. In particular, the regression model is specified as follows:

$$Y_{i,t} = f(\beta_0^{(15)} + \beta_1^{(15)}Trt_k + \beta_2^{(15)}Post_t + \beta_3^{(15)}Trt_k \times Post_t + \eta_i + \zeta_t),$$

and $Trt \times Post$’s coefficient captures the average effect. The estimates are then displayed in Table 24. As is apparent in the table, the SPR entry significantly improves PU sellers’ monthly revenues and listings,
whereas the IPR entry significantly reduces them. Notice that the SPR entrant expands the PU sellers' market more substantially than does the IPR entrant (Table 2). Hence, PU sellers are generally likely to benefit more from the SPR entry than from the IPR entry. Table 24 also shows that both entries have little impact on the price of PU sellers’ listings.

<table>
<thead>
<tr>
<th></th>
<th>Superior Entry</th>
<th></th>
<th></th>
<th>Inferior Entry</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Revenue</td>
<td>(2) Price</td>
<td>(3) # Listings</td>
<td>(4) Revenue</td>
<td>(5) Price</td>
</tr>
<tr>
<td><em>Trt × Post</em></td>
<td>0.843**</td>
<td>0.006</td>
<td>1.065***</td>
<td>-1.078***</td>
<td>-0.123</td>
</tr>
<tr>
<td></td>
<td>(0.421)</td>
<td>(0.216)</td>
<td>(0.348)</td>
<td>(0.244)</td>
<td>(0.151)</td>
</tr>
<tr>
<td><em>Trt</em></td>
<td>1.437***</td>
<td>0.049</td>
<td>0.939***</td>
<td>2.812***</td>
<td>-0.125</td>
</tr>
<tr>
<td></td>
<td>(0.366)</td>
<td>(0.191)</td>
<td>(0.300)</td>
<td>(0.217)</td>
<td>(0.140)</td>
</tr>
<tr>
<td><em>Post</em></td>
<td>-0.975*</td>
<td>-0.564*</td>
<td>-0.579</td>
<td>-0.267</td>
<td>-0.161</td>
</tr>
<tr>
<td></td>
<td>(0.571)</td>
<td>(0.332)</td>
<td>(0.513)</td>
<td>(0.282)</td>
<td>(0.172)</td>
</tr>
<tr>
<td>PU Sellers’ Fixed Effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Month Fixed Effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>578</td>
<td>273</td>
<td>578</td>
<td>3,801</td>
<td>815</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.425</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-678.033</td>
<td>-991.401</td>
<td>-2,596.657</td>
<td>-3,114.752</td>
<td></td>
</tr>
</tbody>
</table>

*Note:* 

Table 24. Entrants’ average effects on PU sellers.

B.6. The Importance of Controlling for Product Characteristics in Comparing Buyer Quality Sensitivities

Using the data simulated from a stylized scenario abstracted from the real data generating process, we demonstrate that controlling for product specifics that affect buyers’ willingness-to-pay (WTP) is crucial to identify buyers’ quality sensitivity differences when we only observe buyers’ WTP for a subset of products (i.e., the products they bid on). This analysis lends support to our choice of using a subset of data with more complete product characteristics in Section 4.3.3 to measure differences in buyers’ quality sensitivities.

Suppose there are \( N \) buyers, each of which bids to their WTP in \( M \) randomly selected auctions. Let half of the buyers belong to type A, whose quality sensitivity is 1, and the remaining half belongs to type B, whose quality sensitivity is 0.5. Half of all auctions are listed by high-quality sellers, whose quality is captured by a value of 10, and the remaining half are listed by low-quality sellers, whose quality is captured by value 6. Each auction contains one product, which is uniformly drawn from 10 product types. Product type \( k \) has a value that is equal to \( 50 \times k \). Then, the WTP of buyer \( i \) for auction \( j \) is determined by:

\[
WTP_{i,j} = ProductValue_j + SensitivityValue_i \times QualityValue_j + \epsilon_{i,j},
\]

where \( \epsilon_{i,j} \sim N(0,1) \).

We observe product types, buyer types, buyers’ WTP, and whether or not a given seller is high quality. Yet, product values and buyers’ quality sensitivities are unobservable. Our goal is to compare quality sensitivities between the two buyer types to determine which type is more sensitive. To demonstrate the importance of
controlling for product types in estimating buyers’ quality sensitivities, we devise the following regression without a product type variable:

\[ \text{WTP}_{i,j} = \beta_0 + \beta_1 \text{BuyerType}_i + \beta_2 \text{SellerType}_j + \beta_3 \text{BuyerType}_i \times \text{SellerType}_j + \epsilon_{i,j}. \]  

(16)

Given the number of listings, \( N \), and the number of listings each buyer participates in, \( M \), we simulate 2,000 random datasets. We then estimate \( \beta_3 \) in Regression (16) using each of these datasets separately, and we calculate the percentage of datasets rendering a significant estimate at significance level 0.1. Figure 6 summarizes the percentage of significant estimates of \( \beta_3 \) for \( N \in \{50, 500, 5,000\} \) and \( M \in \{2, 4, \ldots, 20\} \). As is shown in the figure, Regression (16) cannot identify buyers’ sensitivity differences in most datasets. Although the size of the dataset increases to 100,000 observations, Regression (16)’s estimate is significant in only 30% of the simulated datasets. This finding shows that it is crucial to include product-related covariates when comparing buyers’ sensitivities.

![Figure 6. Percentage of significant estimates of \( \beta_3 \) at level 0.1 among simulated datasets.](image)

*Note: The horizontal dotted line denotes the percentage of significant estimates of \( \beta_3 \) at level 0.1 with the control of product type, which is 100% under all three sample sizes.*
Appendix C: Supplemental Tables and Figures

Figure 7 shows the trend of consumer electronics’ wholesale revenues and the trend of smartphone sales in the United States. Noticeably, there is no jump in these trends within at least one year around the superior and inferior entries (2012-2016). Therefore, our findings in Table 4 are unlikely to be caused by variations in the consumer electronics retail markets.

![Wholesale revenue consumer electronics (CE) shipments in the U.S. from 2009 to 2019 (in billions of U.S. dollars)](image1)

![Smartphone sales in the United States from 2005 to 2019 (in billion U.S. dollars)](image2)

Figure 7. Wholesale revenue of consumer electronics and smartphone sales in the United States.

Figures 8 and 9 provide the snapshots of two cell phone listings in the PU marketplace. Figure 8’s seller has a zero dispute rate, while the seller in Figure 9 has an 8.8% dispute rate. Each listing’s product description is displayed below. We note that the first seller’s description is detailed, while the description provided by the second seller is brief. This suggests that the dispute rate serves as a reliable proxy for the information quality of listings by PU sellers.
Figure 8. Cell phone listing from a PU seller with a 0% dispute rate.
Figure 9. Cell phone listing from a PU seller with an 8.8% dispute rate.
Appendix D: Proofs and Numeric Analysis for Section 5

We first formalize the assumptions under which Observations 1 and 2, as well as Propositions 1, 2, and 3, hold in Appendix D.1. Then, in Appendix D.2, we prove Propositions 1, 2, and 3 by comparing the mass of PU and PR buyers, the supply ratio, and the revenue ratio between the pre-entry and post-entry equilibria, which are characterized in closed form. The derivation of these equilibrium characterizations are presented in the Electronic Companion. Lastly, in Appendix D.3, we numerically and comprehensively examine whether these findings remain in a broad regime.

D.1. Parameter Assumptions

We prove Observations 1 and 2, as well as Propositions 1, 2, and 3, within the parametric region under conditions (i), (ii), and (iii), specified below. It is worth noting that these conditions, which are consistent with the data, are sufficient for our results to hold.

(i) Sensitivity of PU and PR buyers: $\alpha \to 1.5$ (SPR entry), and $\alpha \to 0.5$ (IPR entry).

(ii) PR buyers’ mass: $\mu \in [0.9, 1]$.

(iii) Sellers’ quality: $\{\theta_L, \theta_H, \theta_E\} \subset [1.25, 1.5]$.

In fact, our results hold within a broader parametric region than specified. In Appendix D.3, our findings are numerically examined with these conditions relaxed.

In addition, it is worth mentioning that we are able to characterize all equilibrium quantities before and after a marquee entry (e.g., seller $\theta_H$’s supply after the SPR entry) in closed form that only depends on parameters $\alpha, \mu, \theta_L, \theta_H,$ and $\theta_E$. So, substituting the equilibrium quantities, which are compared in these propositions, with their closed-form characterizations yields the sufficient and necessary conditions of these findings.

D.2. Proofs for Propositions in Section 5 and Supporting Results

In this section we provide proofs of the propositions in §5. In addition we provide the closed-form characterizations for all equilibria involved (e.g., the equilibrium before a PR entry) as well as other results that support our proofs. Their derivations are presented in the Electronic Companion.

To simplify the notation throughout the proofs and the equilibrium characterizations in Appendix D.2, we let $\tau_{i,i'}$ and $\tau_{i,0}$ denote the ratio of the perceived quality difference between two given options among PU and PR buyers. If these two options are sellers $\theta_i$ and $\theta_{i'}$, for $i, i' \in \{L, H, E\}$, then $\tau_{i,i'} = (\theta_i - \theta_{i'}) / (\theta_{\alpha i} - \theta_{\alpha i'}).$ If one of the options is the outside option, then $\tau_{i,0} = \theta_i^{1-\alpha}$, for $i \in \{L, H, E\}$. When characterizing the equilibria, it is crucial to identify threshold PU and PR buyers, who are indifferent between two given options (e.g., PU sellers $\theta_L$ and $\theta_H$). See Appendix EC.2 for an example. Then, $\tau_{i,i'}$ and $\tau_{i,0}$ establish the connections between the threshold PU and PR buyers. Suppose we let $x_{i,i'}$ and $y_{i,i'}$ denote the quality sensitivities of threshold PU and PR buyers, who are indifferent between sellers $\theta_i$ and $\theta_{i'}$. In other words,

$$\theta_i x_{i,i'} - p_i = \theta_{i'} x_{i,i'} - p_{i'} \text{ and } \theta_{\alpha i} y_{i,i'} - p_i = \theta_{\alpha i'} y_{i,i'} - p_{i'}.$$

Then, from the equations above, we obtain $y_{i,i'} = \tau_{i,i'} x_{i,i'}.$ If the given option pair includes the outside option, then we let $x_{i,0}$ and $y_{i,0}$ denote the threshold PU and PR buyers’ sensitivities, respectively. Then, we have

$$\theta_i x_{i,0} - p_i = 0 \text{ and } \theta_{\alpha i} y_{i,0} - p_i = 0,$$
Then, after the superior entry, a pure-strategy Nash equilibrium can be characterized as follows:

**Post-SPR-entry Equilibrium**

In what follows, we outline the two major steps to prove Proposition 5.

**(Pre-entry Equilibrium)**

**Proposition 4** (Pre-entry Equilibrium). Suppose $1 < \theta_L < \theta_H$. Then, a pure-strategy Nash equilibrium before a given entry can be characterized as:

1. **Sellers’ supply**:

   $$Q_{L,0}^* = \frac{\theta_H}{4\theta_H - \theta_L} \text{ and } Q_{H,0}^* = \frac{2\theta_H - \theta_L}{4\theta_H - \theta_L}.$$

2. ** Buyers’ choice**:

   $$\chi_{L,0}^* = [1 - Q_{L,0}^*, 1 - Q_{H,0}^*] \text{ and } \chi_{H,0}^* = [1 - Q_{H,0}^*, 1].$$

3. **Prices**:

   $$p_{L,0}^* = \theta_L(1 - Q_{L,0}^*) \text{ and } p_{H,0}^* = p_{L,0}^* + (\theta_H - \theta_L)(1 - Q_{H,0}^*).$$

See Appendix EC.1 for the proof of Proposition 4.

**Proposition 5** (Post-SPR-entry Equilibrium). Suppose $1 < \theta_L < \theta_H < \theta_E < 1.5$, $\alpha \to 1.5$, and $\mu \in (0, 1)$. Then, after the superior entry, a pure-strategy Nash equilibrium can be characterized as follows:

1. **Sellers’ supply**:

   $$\begin{cases}
   Q_{L,1}^* = \frac{a_1(1 + \mu)}{2(\mu + \rho_{L,0})}, \\
   Q_{H,1}^* = (2 - a_1)Q_{L,1}^*, \\
   Q_{E,1}^* = (4 - a_1 - 2\mu a_1)Q_{L,1}^*, \\
   \end{cases}
   \quad \text{where} \quad
   \begin{cases}
   a_1 = \frac{\theta_L (1 + \mu \tau_{L,0})^{-1}}{\theta_L (1 + \mu \tau_{L,0})^{-1} + (\theta_H - \theta_L)(1 + \mu \tau_{H,L})^{-1}}, \\
   a_2 = \frac{\theta_L (1 + \mu \tau_{L,0})^{-1} + (\theta_H - \theta_L)(1 + \mu \tau_{H,L})^{-1}}{\theta_L (1 + \mu \tau_{L,0})^{-1} + (\theta_H - \theta_L)(1 + \mu \tau_{E,H})^{-1}}.
   \end{cases}(17)$$

2. ** Buyers’ choices**:

   $$\chi_{L,1}^* = \left[\frac{1 + \mu - Q_{L,1}^* - Q_{H,1}^* - Q_{E,1}^*}{1 + \mu - Q_{L,1}^* - Q_{H,1}^* - Q_{E,1}^*}, \frac{1 + \mu - Q_{H,1}^* - Q_{E,1}^*}{1 + \mu - Q_{H,1}^* - Q_{E,1}^*}\right],$$

   $$\chi_{H,1}^* = \left[\frac{1 + \mu - Q_{L,1}^* - Q_{E,1}^*}{1 + \mu - Q_{L,1}^* - Q_{E,1}^*}, \frac{1 + \mu - Q_{H,1}^* - Q_{E,1}^*}{1 + \mu - Q_{H,1}^* - Q_{E,1}^*}\right],$$

   $$\chi_{E,1}^* = \left[\frac{1 + \mu - Q_{E,1}^*}{1 + \mu - Q_{E,1}^*}, 1\right],$$

   $$\gamma_{L,1}^* = \left[\frac{1 + \mu - Q_{L,1}^*}{1 + \mu - Q_{L,1}^*}, 1\right],$$

   $$\gamma_{H,1}^* = \left[\frac{1 + \mu - Q_{H,1}^*}{1 + \mu - Q_{H,1}^*}, 1\right],$$

   $$\gamma_{E,1}^* = \left[\frac{1 + \mu - Q_{E,1}^*}{1 + \mu - Q_{E,1}^*}, 1\right].$$

3. **Prices**:

   $$\begin{cases}
   p_{L,1}^* = \frac{\theta_L}{1 + \mu \tau_{L,0}}(1 + \mu - Q_{L,1}^* - Q_{H,1}^* - Q_{E,1}^*), \\
   p_{H,1}^* = p_{L,1}^* + \frac{\theta_L - \theta_H}{1 + \mu \tau_{H,L}}(1 + \mu - Q_{H,1}^* - Q_{E,1}^*), \\
   p_{E,1}^* = p_{H,1}^* + \frac{\theta_L - \theta_H}{1 + \mu \tau_{E,H}}(1 + \mu - Q_{E,1}^*),
   \end{cases}(19)$$

In what follows, we outline the two major steps to prove Proposition 5.
First, we verify that it is optimal for buyers in each set specified by Expression (18) to choose the corresponding seller under the prices given by Expression (19). In addition, for each type of seller, we show that the demand (i.e., the mass of customer sets specified by Expression (18)) is equal to the supply given by Expression (17).

Second, we establish the optimality of sellers’ supply characterized by Expression (17). In particular, we show that $Q_{E,1}^*, Q_{L,1}^*$, and $Q_{H,1}^*$ maximize the revenues of PU seller $\theta_L$, PU seller $\theta_H$, and the PR seller, respectively, given that others’ supply follows Expression (17). We note that the given seller’s revenue is piece-wise concave in its supply. So, first-order conditions cannot be applied to solving the optimal supply. Alternatively, we establish the optimality of the characterized supply by searching through all optimal solutions within each concave region.

The detailed argument of each step and the complete proof can be found in Appendix EC.2. Similar steps are also followed in proving the following propositions (i.e., Propositions 6, 7, and 8).

**Proposition 6** (Post-IPR-entry Equilibrium). Suppose $1 < \theta_E < \theta_L < \theta_H < 1.5$, $\alpha \to 0.5$, and $\mu \in (0.2, 1)$. Then, after the inferior entry, a pure-strategy Nash equilibrium can be characterized as follows:

1. **Sellers’ supply:**

   $$\begin{align*}
   Q_{E,1}^* &= \frac{a_1}{2(4a_1 - a_2 - a_1^2)} \left(1 + \frac{2 - a_2}{a_1} \mu \right), \\
   Q_{L,1}^* &= \frac{a_1}{2(4a_1 - a_2 - a_1^2)} \left(1 + \frac{2 - a_2}{a_1} \mu \right)(2 - a_1), \\
   Q_{H,1}^* &= \frac{a_1}{2(4a_1 - a_2 - a_1^2)} \left(4 - a_1 - \frac{2a_2}{a_1} + (2 - a_1) \frac{a_2}{a_1} \mu \right),
   \end{align*}$$

   where

   $$\begin{align*}
   a_1 &= \frac{\theta_E (1 + \mu \tau_{E,0})^{-1}}{\theta_E (1 + \mu \tau_{E,0})^{-1} + (\theta_L - \theta_E)(1 + \mu \tau_{L,E})^{-1}}, \\
   a_2 &= \frac{\theta_E (1 + \mu \tau_{E,0})^{-1} + (\theta_L - \theta_E)(1 + \mu \tau_{L,E})^{-1}}{\theta_E (1 + \mu \tau_{E,0})^{-1} + (\theta_L - \theta_E)(1 + \mu \tau_{L,E})^{-1} - (\theta_H - \theta_L)}.
   \end{align*}$$

2. **Buyers’ choices:**

   $$\begin{align*}
   X_{E,1}^* &= \left[\frac{1 + \mu - Q_{E,1}^* - Q_{L,1}^* - Q_{H,1}^*}{1 + \mu \tau_{E,0}}, \frac{1 + \mu - Q_{E,1}^* - Q_{L,1}^* - Q_{H,1}^*}{1 + \mu \tau_{L,E}} \right], \\
   Y_{E,1}^* &= \left[\frac{1 - Q_{E,1}^*}{1 + \mu \tau_{E,0} + \mu}, \frac{1 - Q_{E,1}^*}{1 + \mu \tau_{L,E} + \mu} \right], \\
   X_{L,1}^* &= \left[\frac{1 + \mu - Q_{L,1}^* - Q_{H,1}^*}{1 + \mu \tau_{L,E}}, 1 - Q_{H,1}^* \right], \\
   Y_{L,1}^* &= \left[\frac{1 - Q_{L,1}^*}{1 + \mu \tau_{L,E} + \mu}, 1 \right], \\
   X_{H,1}^* &= \left[1 - Q_{H,1}^*, 1 \right], \\
   Y_{H,1}^* &= \emptyset.
   \end{align*}$$

3. **Prices:**

   $$\begin{align*}
   p_{E,1}^* &= \frac{\theta_E}{1 + \mu \tau_{E,0}} (1 + \mu - Q_{E,1}^* - Q_{L,1}^* - Q_{H,1}^*), \\
   p_{L,1}^* &= p_{E,1}^* + (\theta_L - \theta_E) \frac{1 + \mu - Q_{E,1}^* - Q_{L,1}^* - Q_{H,1}^*}{1 + \mu \tau_{L,E}}, \\
   p_{H,1}^* &= p_{L,1}^* + (\theta_H - \theta_L)(1 - Q_{H,1}^*).
   \end{align*}$$

The proof follows the same argument as in Proposition 5’s proof, so we omit it for brevity.

**Proof for Observation 1**

The proof proceeds as follows. We first establish the localized market stealing and the localized market expansion under the SPR entry. Then, we show these two effects under the IPR entry.

**SPR entry.**

Under the SPR entry, these two localized market effects translate to the fact that the high-quality PU seller loses more of their pre-entry buyers to the SPR entrant and attracts more PR buyers from the latter than does the low-quality PU seller. In other words, the following inequalities need to hold:

$$\begin{align*}
&\lambda(X_{H,0}^* \cap X_{E,1}^*) > \lambda(X_{L,0}^*) \quad \lambda(X_{E,1}^* \cap X_{L,0}^*), \\
&\lambda(Y_{H,1}^*) > \lambda(Y_{L,1}^*).
\end{align*}$$

**References:**

Title: Marketplace Expansion through Marquee Seller Adoption
where PU buyers’ pre-entry choices \(\lambda^*_{L,0}\) and \(\lambda^*_{H,0}\) are characterized by Proposition 4, and PU buyers’ post-entry choices \(\lambda^*_{L,1}\), \(\lambda^*_{H,1}\), and \(\lambda^*_{E,1}\), as well as PR buyers’ choices \(\gamma^*_{L,1}\) and \(\gamma^*_{H,1}\), are characterized by Proposition 5.

First, we show that inequality (22) holds. Using the structure of buyers’ equilibrium choices characterized by Propositions 4 and 5, we observe that seller \(\theta_L\) will lose some of their pre-entry buyers to the PR entrant (i.e., \(\lambda(\lambda^*_{L,0} \cap \lambda^*_{E,1}) > 0\)) if and only if seller \(\theta_H\) loses all their pre-entry buyers to the entrant (i.e., \(\lambda(\lambda^*_{H,0} \cap \lambda^*_{E,1}) = \lambda(\lambda^*_{H,0})\)). This is due to sorting of PU buyers across \(\theta_L\) and \(\theta_H\) sellers by their quality sensitivities. Thus, the following two conditions hold:

1. \(\lambda(\lambda^*_{H,0} \cap \lambda^*_{E,1})/\lambda(\lambda^*_{H,0}) < 1\) if and only if \(\lambda(\lambda^*_{L,0} \cap \lambda^*_{E,1})/\lambda(\lambda^*_{L,0}) = 0\).
2. \(\lambda(\lambda^*_{H,0} \cap \lambda^*_{E,1})/\lambda(\lambda^*_{H,0}) = 1\) if and only if \(\lambda(\lambda^*_{L,0} \cap \lambda^*_{E,1})/\lambda(\lambda^*_{L,0}) \geq 0\).

The above imply inequality (22) in weak form. To show that Inequality (22) strictly holds is equivalent to showing that

\[
\lambda(\lambda^*_{H,0} \cap \lambda^*_{E,1}) > 0, \text{ and } \lambda(\lambda^*_{L,0} \cap \lambda^*_{E,1})/\lambda(\lambda^*_{L,0}) < 1.
\]

The inequalities above combined with the previous statement would rule out the possibility of \(\lambda(\lambda^*_{H,0} \cap \lambda^*_{E,1})/\lambda(\lambda^*_{E,0}) = \lambda(\lambda^*_{L,0} \cap \lambda^*_{E,1})/\lambda(\lambda^*_{L,0})\). Intuitively the two sets of conditions we need to show require the entrant to be of moderate quality so that they attract some of the high-quality PU sellers’ buyers, but does not steal all of the PU sellers’ buyers. The first inequality above, \(\lambda(\lambda^*_{H,0} \cap \lambda^*_{E,1}) > 0\), follows by the characterizations of \(\lambda^*_{H,0}\) (Proposition 4) and \(\lambda^*_{E,1}\) (Proposition 5), which indicate that the most quality-sensitive PU buyers switch from seller \(\theta_H\) to the entrant post-entry. To show the second inequality above, we note that

\[
\inf \lambda^*_{L,0} = 1 - Q^*_{L,0} - Q^*_{H,0} = \frac{\theta_H}{4\theta_H - \theta_L} < \frac{1}{3} < \frac{1 + \mu - Q^*_{E,1}}{1 + \mu \tau_{E,H}} = \inf \lambda^*_{E,1}.
\]

In particular, \(\frac{\theta_H}{4\theta_H - \theta_L} < \frac{1}{3}\) is equivalent to \(\theta_L < \theta_H\), which is true. Then, to show \(\frac{1}{3} < \frac{1 + \mu - Q^*_{E,1}}{1 + \mu \tau_{E,H}}\), it suffices to show that \(Q^*_{E,1} < \frac{2}{3}(1 + \mu)\) (i.e., the SPR entrant’s supply serves less than two thirds of the market).

By algebra, we can show that the last inequality follows given \(Q^*_{E,1}\)’s characterization in Proposition 5 and \(\tau_{E,H} < 1\) by Lemma 1 earlier. Therefore, we have established inequality (22).

Second, to show inequality (23), or equivalently \(\lambda(\gamma^*_{H,1})/\lambda(\gamma^*_{L,1}) > 1\), we aim to find a lower bound of the last ratio that is greater than 1. In particular, we claim that it holds if \(\lambda(\lambda^*_{H,1})/\lambda(\lambda^*_{L,1}) < \lambda(\gamma^*_{H,1})/\lambda(\gamma^*_{L,1})\). We prove the claim by contradiction. Suppose \(\lambda(\gamma^*_{H,1}) \leq \lambda(\gamma^*_{L,1})\) holds (i.e., inequality (23) is invalid) under \(\lambda(\lambda^*_{H,1})/\lambda(\lambda^*_{L,1}) < \lambda(\gamma^*_{H,1})/\lambda(\gamma^*_{L,1})\). Then, we obtain

\[
\frac{\lambda(\lambda^*_{H,1})}{\lambda(\lambda^*_{L,1})} < \frac{\lambda(\gamma^*_{H,1})}{\lambda(\gamma^*_{L,1})} \leq 1,
\]

implying that \(\lambda(\lambda^*_{H,1}) < \lambda(\lambda^*_{L,1})\). That is, \(Q^*_{H,1} = \lambda(\lambda^*_{H,1}) + \mu \lambda(\gamma^*_{H,1}) < \lambda(\lambda^*_{L,1}) + \mu \lambda(\gamma^*_{L,1}) = Q^*_{L,1}\). However, by the characterizations of \(Q^*_{L,1}\) and \(Q^*_{H,1}\) in Proposition 5, the last inequality indicates that \(a_1 > 1\), which is not true and, thus, the contradiction.
To complete the argument, we next establish that \( \lambda(Y_{H,1}^*)/\lambda(Y_{L,1}^*) > \lambda(X_{H,1}^*)/\lambda(X_{L,1}^*) \), where \( X_{L,1}^*, X_{H,1}^* \), \( Y_{L,1}^* \), and \( Y_{H,1}^* \) are characterized by Expression (18). By substituting \( X_{L,1}^*, X_{H,1}^* \), \( \lambda(Y_{L,1}^*) \), and \( \lambda(Y_{H,1}^*) \) in the inequality, we obtain that we need to equivalently prove:

\[
\frac{(2 - a_1/2) \frac{\tau_{E,H}}{1 + \mu \tau_{E,H}}}{(2 - a_1/2) \frac{1}{1 + \mu \tau_{E,H}}} > \frac{\tau_{H,L}}{1 + \mu \tau_{H,L}} - \frac{\tau_{L,0}}{1 + \mu \tau_{L,0}}.
\]

(24)

To show inequality (24), we first define the following auxiliary function:

\[
f_{l,u}(x) = \frac{\tau_{E,H}}{1 + \mu \tau_{E,H}} x - \frac{\tau_{H,L}}{1 + \mu \tau_{H,L}} x.
\]

Then, the left side of inequality (24) is equal to \( f_{l,u}(2 - a_1/2) \). Note that \( f_{l,u}(x) \) has the same sign as \( \tau_{H,L}/\tau_{E,H} - 1 \), which is positive (by Lemma 1). Since \( 0 < a_1 < 1 \), the left side of inequality (24),

\[
\frac{(2 - a_1/2) \frac{\tau_{E,H}}{1 + \mu \tau_{E,H}}}{(2 - a_1/2) \frac{1}{1 + \mu \tau_{E,H}}} = \frac{\tau_{E,H}}{1 + \mu \tau_{E,H}} - \frac{\tau_{H,L}}{1 + \mu \tau_{H,L}},
\]

should be no less than \( f_{l,u}(3/2) \). Then, to show inequality (24), it suffices to show:

\[
\frac{3}{2} \frac{\tau_{E,H}}{1 + \mu \tau_{E,H}} - \frac{\tau_{H,L}}{1 + \mu \tau_{H,L}} = \frac{\tau_{E,H}}{1 + \mu \tau_{E,H}} - \frac{\tau_{H,L}}{1 + \mu \tau_{H,L}} - \frac{\tau_{L,0}}{1 + \mu \tau_{L,0}} > 0.
\]

Applying the same argument as we use to show inequality (EC.8), we can show that the inequality above holds under \( \alpha = 1.5, 1.25 < \theta_L < \theta_H < \theta_E < 1.5 \), and \( \mu \in (0,1) \) (i.e., establishing that there is a positive lower bound of the above inequality’s left side based on its Lipschitz continuity and its minimum value over a grid of the given parametric space). We omit the details for brevity (proof for inequality (EC.8) has relevant details). By the continuity of the inequality’s left side with respect to \( \alpha \), we conclude the inequality holds for \( \alpha \rightarrow 1.5 \). Therefore, inequality (23) has been proven, and this completes the argument for the SPR entry.  

**IPR entry.**

In this case, the two localized market effects translate to the fact that the low-quality PU seller loses more of their pre-entry buyers to the IPR entrant and attracts more PR buyers from the latter than does the high-quality PU seller. In other words, the following inequalities need to hold:

\[
\text{(Localized market stealing)} \quad \frac{\lambda(X_{L,0}^* \cap X_{E,1}^*)}{\lambda(X_{L,0}^*)} > \frac{\lambda(X_{H,0}^* \cap X_{E,1}^*)}{\lambda(X_{H,0}^*)} \tag{25}
\]

\[
\text{(Localized market expansion)} \quad \lambda(Y_{L,1}^*) > \lambda(Y_{H,1}^*), \tag{26}
\]

where PU buyers’ pre-entry choices \( X_{L,0}^* \) and \( X_{H,0}^* \) are characterized by Proposition 4, and PU buyers’ post-entry choices \( X_{L,1}^* \), \( X_{H,1}^* \), and \( X_{E,1}^* \), as well as PR buyers’ choices \( Y_{L,1}^* \) and \( Y_{H,1}^* \), are characterized by Proposition 5.

First, we show that inequality (25) holds. We claim that more PU buyers transact with sellers on the platform after the entry than those before the entry. In other words, \( \inf X_{E,1}^* < \inf X_{L,0}^* \), where \( X_{E,1}^* \) and \( X_{L,0}^* \) are characterized by Propositions 4 and 6, respectively. After substituting \( X_{L,1}^* \) and \( X_{H,0}^* \) in the last inequality with their characterizations and rearranging the inequality, we obtain the following:

\[
(1 + \mu \tau_{E,0})^{-1} \frac{1 + \left( 2 - \frac{2 \mu}{a_1} \right) \mu}{2 \left( 4 - \frac{2 \mu}{a_1} - a_1 \right)} \frac{\theta_H}{4 \theta_H - \theta_L} < \frac{\theta_H}{4 \theta_H - \theta_L}.
\]
The inequality above holds because its right side is greater than $\frac{1}{4}$, and its left side is less than $\frac{1}{4}$. Thus, the claim holds.

Using the claim above and the structure of buyers’ equilibrium choices described by Propositions 4 and 6, we obtain a similar observation as that under the SPR entry: Seller $\theta_H$ will lose their pre-entry buyers to the PR entrant (i.e., $\lambda(X_{H,0}^* \cap X_{E,1}^*) > 0$) if and only if seller $\theta_E$ loses all their pre-entry buyers to the entrant (i.e., $\lambda(X_{L,0}^* \cap X_{E,1}^*) = \lambda(X_{L,0}^*)$). That is,

- $\lambda(X_{L,0}^* \cap X_{E,1}^*)/\lambda(X_{L,0}^*) < 1$ if and only if $\lambda(X_{H,0}^* \cap X_{E,1}^*)/\lambda(X_{H,0}^*) = 0$.
- $\lambda(X_{L,0}^* \cap X_{E,1}^*)/\lambda(X_{L,0}^*) = 1$ if and only if $\lambda(X_{H,0}^* \cap X_{E,1}^*)/\lambda(X_{H,0}^*) \geq 0$.

Note that $\lambda(X_{H,0}^* \cap X_{E,1}^*) < \lambda(X_{H,0}^*)$ follows because not all PU buyers choose the IPR entrant (this relies on our assumption of entrant quality being moderate). Then, inequality (25) holds if and only if $\lambda(X_{L,0}^* \cap X_{E,1}^*) > 0$, to rule out the possibility of $\lambda(X_{L,0}^* \cap X_{E,1}^*)/\lambda(X_{L,0}^*) = \lambda(X_{H,0}^* \cap X_{E,1}^*)/\lambda(X_{H,0}^*)$. We note that $\lambda(X_{L,0}^* \cap X_{E,1}^*) > 0$ holds because we can show that:

$$\inf \lambda_{L,0} = 1 - Q_{L,0} - Q_{H,0} = \frac{\theta_H}{4\theta_L - \theta_E} < \frac{1}{3} < \frac{1}{1 + \mu - Q_{L,1} - Q_{H,1}} = \sup \lambda_{E,1}.$$ 

In particular, using $Q_{L,1}^*$ and $Q_{H,1}^*$’s characterizations (Proposition 6), the last inequality in the expression above is equivalent to:

$$\frac{3}{2} \frac{5a_1 - a_2 + (2a_1 + 2a_2 + a_1^2 - a_1a_2)}{4a_1 - a_2 - a_1^2} > 1 + \mu \tau_{L,E},$$

which we can prove using straightforward algebra. Therefore, we have shown that $\lambda(X_{L,0}^* \cap X_{E,1}^*) > 0$, and inequality (25) hence holds.

Second, we show that inequality (26) holds. In fact, the inequality immediately follows under the IPR entry, because $Y_{H,1}^* = \emptyset$ and $Y_{L,1}^* \neq \emptyset$ by Proposition 6.

This completes the proof for Observation 1. □

33 To show $(1 + \mu \tau_{E,0}) a_1^2 + (2 - \frac{a_2}{a_1}) \mu < \frac{1}{4}$, it suffices to show $(1 + \mu)^{-1} \frac{1 + (2 - \frac{a_2}{a_1}) \mu}{2 (4 - \frac{a_2}{a_1} - a_1)} < \frac{1}{4}$, which is equivalent to $a_2 < a_1$.

34 By Lemma 4 (Appendix EC.3), we have $\tau_{L,E} < \frac{5}{2} (\text{note that } \bar{\theta} = 1.5)$. Then, to show the inequality above, it suffices to show that:

$$\frac{3}{2} \frac{5a_1 - a_2 + (2a_1 + 2a_2 + a_1^2 - a_1a_2)}{4a_1 - a_2 - a_1^2} > 1 + \mu \tau_{L,E},$$

which is equivalent to $7a_1 - a_2 + 2a_1^2 > (14a_1 - 11a_2 - 8a_1^2 + 3a_1a_2) \mu$. The inequality above holds immediately if its right side is negative (note that its left side is always positive). However, if its right side is positive, it suffices to show that $7a_1 - a_2 + 2a_1^2 > 14a_1 - 11a_2 - 8a_1^2 + 3a_1a_2$ as $\mu < 1$, which is equivalent to $10a_2 + 10a_1^2 > 7a_1 + 3a_1a_2$. To show the last inequality, it suffices to show that $\frac{a_2}{a_1} > 1 - a_1$ since $a_1 > a_2$. By the characterizations of $a_1$ and $a_2$, $\frac{a_2}{a_1} > 1 - a_1$ is equivalent to

$$\frac{\theta_E}{\theta_L - \theta_E} \frac{1 + \mu \tau_{L,E}}{1 + \mu \tau_{E,0}} + 1 > \left( \frac{\theta_E}{\theta_L - \theta_E} \frac{1 + \mu \tau_{L,E}}{1 + \mu \tau_{E,0}} + 1 \right) + \frac{\theta_H - \theta_L}{\theta_L - \theta_E} (1 + \mu \tau_{L,E}).$$

Inequality (27) holds because

$$\frac{\theta_E}{\theta_L - \theta_E} \frac{1 + \mu \tau_{L,E}}{1 + \mu \tau_{E,0}} > \frac{\theta_H - \theta_L}{\theta_L - \theta_E} (1 + \mu \tau_{L,E}),$$

which is equivalent to $\frac{\theta_E}{\theta_H - \theta_E} > 1 + \mu \tau_{E,0}$. It is straightforward to verify that the last inequality holds under $1 < \theta_E < \theta_L < \theta_H < 1.5$, $\mu < 1$, and $0.5 < \mu < 1$. 
Proof for Observation 2

The proof consists of two parts. In the first part, we establish that under the SPR entry, seller $\theta_H$'s supply expands and revenue increases relative to seller $\theta_L$ (i.e., $Q_{H,1}/Q_{H,0} > Q_{L,1}/Q_{L,0}$ and $\pi_{H,1}/\pi_{H,0} > \pi_{L,1}/\pi_{L,0}$). In the second part, we establish that under the IPR entry, these effects are reversed (i.e., $Q_{L,1}/Q_{L,0} > Q_{H,1}/Q_{H,0}$ and $\pi_{L,1}/\pi_{L,0} > \pi_{H,1}/\pi_{H,0}$).

**SPR entry.**

For seller $\theta_H$'s relative supply expansion, it is straightforward to verify that $Q_{H,1}/Q_{H,0} > Q_{L,1}/Q_{L,0}$ is equivalent to $\tau_{H,L} < \tau_{L,0}$, which holds because of Lemma 1. Next, showing seller $\theta_H$'s relative revenue increase is equivalent to showing $\pi_{H,1}/\pi_{H,0} = (p_{H,1}Q_{H,1})/(p_{L,1}Q_{L,1}) > (p_{H,0}Q_{H,0})/(p_{L,0}Q_{L,0}) = \pi_{H,0}/\pi_{L,0}$. Given that $Q_{H,1}/Q_{L,1} > Q_{H,0}/Q_{L,0}$ has been shown, it suffices to show that $p_{H,1}/p_{L,1} > p_{H,0}/p_{L,0}$. Note that Proposition 4 implies $p_{H,0}/p_{L,0} = 2\theta_H/\theta_L - 1$ before entry. Also, Proposition 5 implies that after the SPR entry,

$$\frac{p_{H,1}}{p_{L,1}} = 1 + 2 \left( \frac{\theta_H}{\theta_L} - 1 \right) \cdot \frac{1 + \mu \tau_{L,0}}{1 + \mu \tau_{H,L}}.$$ 

These two identities imply that $p_{H,1}/p_{L,1} > p_{H,0}/p_{L,0}$ is equivalent to $\tau_{L,0} > \tau_{H,L}$, which holds due to Lemma 1. This proves that seller $\theta_H$ has a relative revenue benefit under the SPR entry.

**IPR entry.**

By Propositions 4 and 6, we have

$$\frac{Q_{L,0}}{Q_{H,0}} = \left( 2 - \frac{\theta_L}{\theta_H} \right)^{-1} \quad \text{and} \quad \frac{Q_{H,1}}{Q_{L,1}} = \left( 1 + 2 \left( 1 - \frac{a_2}{a_1} \right) \left( 2 - a_1 \right)^{-1} - \mu \right)^{-1}.$$  

To show seller $\theta_L$'s relative supply expansion compared to seller $\theta_H$ (i.e., $Q_{L,1}/Q_{L,0} > Q_{H,1}/Q_{H,0}$) is equivalent to

$$\frac{\theta_L - \theta_H}{\frac{1}{1 + \mu \tau_{L,E}} + \frac{\theta_L - \theta_E}{1 + \mu \tau_{L,E}} + \frac{\theta_H - \theta_L}{1 + \left( 2 - \frac{a_2}{a_1} \right) \mu} - \frac{1}{\theta_H} < 0.$$  

Applying a similar argument as we show in inequality (EC.8), we can show that the inequality above holds for $\alpha = 0.5, 0.9 < \mu < 1$, and $1.25 < \theta_E < \theta_L < \theta_H < 1.5$ (i.e., establishing that there is a negative upper bound of the above inequality’s left side based on its Lipschitz continuity and its maximum value over a grid of the given parametric space). We omit the details for brevity. By the continuity of the inequality’s left side with respect to $\alpha$, we conclude that the inequality holds for $\alpha \to 0.5$. This proves the supply expansion result for the IPR entry.

Next we show seller $\theta_L$’s relative revenue increase as compared to seller $\theta_H$ (i.e., $\pi_{L,1}/\pi_{L,0} > \pi_{H,1}/\pi_{H,0}$). Using the characterizations of $Q_{i,t}^*$ for $i \in \{L, H\}$ and $t \in \{0, 1\}$ in Propositions 4 and 6, we have:

$$\frac{Q_{L,1}}{Q_{H,1}} \frac{Q_{H,0}}{Q_{L,0}} = \frac{1 + (\theta_H - \theta_L)A_1}{1 + (\theta_H - \theta_L)A_2},$$

where

$$A_1 \triangleq \frac{1}{\theta_H} \quad \text{and} \quad A_2 \triangleq \frac{2 \left( \frac{1 - \mu \tau_{L,E}}{1 + (2 - \frac{a_2}{a_1}) \mu} \right)}{\theta_E (1 + \mu \tau_{E,0})^{-1} + (\theta_L - \theta_E) (1 + \mu \tau_{L,E})^{-1} + (\theta_H - \theta_L)}.$$
Also, using the characterizations of $p^*_i, t \in \{L, H\}$ for $i \in \{L, H\}$ and $t \in \{0, 1\}$ in Propositions 4 and 6, we obtain

$$
\frac{p^*_H,1}{p^*_L,0}, \frac{p^*_L,0}{p^*_H,0} = \frac{1 + (\theta_H - \theta_L)B_1}{\frac{a_H}{\theta_L} + (\theta_H - \theta_L)B_2},
$$

where

$$
B_1 \equiv \frac{4 - a_1 - a_2 \left(\frac{a_2}{a_1} - 1\right)}{2 + \frac{a_H - a_L}{\theta_H - \theta_L}}, \quad \frac{a_H}{\theta_L} + (\theta_H - \theta_L), \quad \text{and } B_2 = \frac{1}{\theta_L}.
$$

Then to prove our result, which is $\pi^*_L,1/\pi^*_H,1 = (p^*_L,1, Q^*_L,1)/(p^*_H,1, Q^*_H,1) > (p^*_L,0, Q^*_L,0)/(p^*_H,0, Q^*_H,0) = \pi^*_L,0/\pi^*_H,0$, is equivalent to

$$
3B_2 + (\theta_H - \theta_L)(A_2B_2 - A_2B_1) - (A_2 + B_1) > 0.
$$

Applying the same argument as we show in inequality (EC.8), we can show that the inequality above holds for $\alpha = 0.5, 0.9 \leq \mu < 1$, and $1.25 < \theta_E < \theta_L < \theta_H < 1.5$ (i.e., establishing that there is a positive lower bound of the above inequality’s left side based on its Lipschitz continuity and its minimum value over a grid of the given parametric space). We omit the details for brevity. By the continuity of the inequality’s left side with respect to $\alpha$, we conclude that the inequality holds for $\alpha \to 0.5$.

This completes the proof for Observation 2. \hfill \Box

Before we present the proof for Proposition 1, we outline, in the following proposition, the equilibria for the counterfactual scenario when PU sellers cannot change their supply after the marquee entry.

**Proposition 7** (Post-entry Equilibrium Without Supply Responses). Suppose PU sellers do not adjust their supply after a given entry (i.e., $Q_{L,1,NR} = Q^*_{L,0}$ and $Q_{H,1,NR} = Q^*_{H,0}$) and $\mu \in (0, 1)$. Then,

- After the superior entry (i.e., $1 < \theta_L < \theta_E < \theta_H < 1.5$ and $\alpha \to 1.5$), a pure-strategy Nash equilibrium can be characterized as follows:
  
  \begin{itemize}
  \item Entrant’s supply:
  
  $$
  Q^*_{E,1,NR} = \frac{1}{2} \left(1 + \mu - \frac{a_H}{1 + \mu} Q_{L,1,NR} + \left(\frac{a_H}{1 + \mu} + \frac{a_H - a_L}{1 + \mu - \theta_L} Q_{H,1,NR}\right)ight).
  $$
  
  \item Buyers’ choices follow the same characterizations as Equation (18), with $Q^*_{L,1}, Q^*_{H,1}$, and $Q^*_{E,1}$ substituted with $Q_{L,1,NR}, Q_{H,1,NR}$, and $Q^*_{E,1,NR}$, respectively.
  
  \item The prices follow the same characterizations as Equation (19), with $Q^*_{L,1}, Q^*_{H,1}$, and $Q^*_{E,1}$ substituted with $Q_{L,1,NR}, Q_{H,1,NR}$, and $Q^*_{E,1,NR}$, respectively.
  
  \end{itemize}

- After the inferior entry (i.e., $1 < \theta_E < \theta_L < \theta_H < 1.5$ and $\alpha \to 0.5$), a pure-strategy Nash equilibrium can be characterized as follows:
  
  \begin{itemize}
  \item Entrant’s supply:
  
  $$
  Q^*_{E,1,NR} = \frac{1}{2} \left(1 + \mu - Q_{L,1,NR} - Q_{H,1,NR}\right).
  $$
  
  \item Buyers’ choices follow the same characterizations as Equation (20), with $Q^*_{E,1}, Q^*_{L,1}$, and $Q^*_{H,1}$ substituted with $Q^*_{E,1,NR}, Q_{L,1,NR}$, and $Q_{H,1,NR}$, respectively.
  
  \item The prices follow the same characterizations as Equation (21), with $Q^*_{E,1}, Q^*_{L,1}$, and $Q^*_{H,1}$ substituted with $Q^*_{E,1,NR}, Q_{L,1,NR}$, and $Q_{H,1,NR}$, respectively.
  
  \end{itemize}

The proof follows the same argument as shown in Proposition 5’s proof, so we omit it for brevity.
Proof for Proposition 1

Again, we prove the result in two parts. First we show the result for the SPR entry and then for the IPR entry.

**SPR entry.**

Here, we show that when sellers cannot adjust their supply quantities after the SPR marquee entry, seller \( \theta_H \)'s revenue is worse off relative to seller \( \theta_L \)'s (i.e., \( \pi_{H,1,NR}/p^*_{H,0} < \pi_{L,1,NR}/p^*_{L,0} \) holds). Given the absence of supply response, we note that the revenue-based inequality above is equivalent to the price-based inequality, \( p_{H,1,NR}/p^*_{H,0} < p_{L,1,NR}/p^*_{L,0} \). Substituting \( p^*_{L,0}, p^*_{H,0}, p_{L,1,NR}, \) and \( p_{H,1,NR} \) in the last inequality by their characterizations given by Propositions 4 and 7, we obtain:

\[
\frac{1 + \mu \tau_{L,0}}{1 + \mu \tau_{H,L}} \left( \frac{1 + \mu - Q^*_{H,0} - Q^*_{E,1,NR}}{1 + \mu - Q^*_{L,0} - Q^*_{E,1,NR}} - 2 \right) < 0.
\]

Applying a similar argument as we show in inequality (EC.8), we can show that the inequality above holds for \( \alpha = 1.5, 0.9 \leq \mu < 1, \) and \( 1.25 < \theta_E < \theta_L < \theta_H < 1.5 \) (i.e., establishing that there is a negative upper bound of the above inequality’s left side based on its Lipschitz continuity and its maximum value over a grid of the given parametric space). We omit the details for brevity. By the continuity of the inequality’s left side with respect to \( \alpha \), we conclude that it holds for \( \alpha \to 1.5 \).

**IPR entry.**

Next, we show that seller \( \theta_L \)'s revenue is worse off then seller \( \theta_H \)'s (i.e., \( \pi_{L,1,NR}/p^*_{L,0} < \pi_{H,1,NR}/p^*_{H,0} \)) under the IPR entry. Absent supply responses, we note that the inequality above is equivalent to \( p_{L,1,NR}/p^*_{L,0} < p_{H,1,NR}/p^*_{H,0} \). Substituting \( p^*_{L,0}, p^*_{H,0}, p_{L,1,NR}, \) and \( p_{H,1,NR} \) in the last inequality by their characterizations given by Propositions 4 and 7, we obtain:

\[
\frac{1}{2} \left( \frac{\theta_E}{1 + \mu \tau_{E,0}} + \frac{\theta_L - \theta_E}{1 + \mu \tau_{L,E}} - \frac{\theta_H \theta_L}{\mu (4 \theta_H - \theta_L) + \theta_H} \right) < 0.
\]

Applying a similar argument as we show in inequality (EC.8), we can show that the inequality above holds for \( \alpha = 0.5, 0.9 \leq \mu < 1, \) and \( 1.25 < \theta_E < \theta_L < \theta_H < 1.5 \) (i.e., establishing that there is a negative upper bound of the above inequality’s left side based on its Lipschitz continuity and its maximum value over a grid of the given parametric space). We omit the details for brevity. By the continuity of the inequality’s left side with respect to \( \alpha \), we conclude that it holds for \( \alpha \to 0.5 \).

This completes the proof for Proposition 7. \( \Box \)

In the proposition below, we outline the equilibria for the counterfactual scenario of PR buyers of either quality having the same quality sensitivity as PU buyers.

**Proposition 8** (Post-entry Equilibrium With Static Demand Composition). Suppose \( \alpha = 1 \) and \( \mu \in (0,1) \).

Then,

- After the superior entry (i.e., \( 1 < \theta_L < \theta_H < \theta_E < 1.5 \)), a pure-strategy Nash equilibrium can be characterized as follows:
  - Sellers' supply:
    \[
    Q_{L,1}^* = \frac{1 + \mu}{2 \left( 4 - \frac{\theta_E}{\theta_H} - \frac{\theta_L}{\theta_E} \right)}, \quad Q_{H,1}^* = \left( 2 - \frac{\theta_L}{\theta_H} \right) Q_{L,1}^*, \quad \text{and} \quad Q_{E,1}^* = \left( 4 - \frac{\theta_L}{\theta_H} - \frac{2 \theta_H}{\theta_E} \right) Q_{L,1}^*.
    \]
- Buyers’ choices:

\[ X^*_L,1 = Y^*_L,1 = \left[ \frac{1}{2 \left( 4 - \frac{\theta_L}{\theta_E} - \frac{\theta_M}{\theta_E} \right)}, \frac{1}{4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E}} \right], \]

\[ X^*_H,1 = Y^*_H,1 = \left[ \frac{1}{4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E}}, \frac{1}{2 \left( 4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E} \right)} \right], \]

and \[ X^*_E,1 = Y^*_E,1 = \left[ \frac{4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E}}{2 \left( 4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E} \right)}, 1 \].

- Prices:

\[ p^*_L,1 = \frac{\theta_L}{2 \left( 4 - \frac{\theta_L}{\theta_E} - \frac{\theta_M}{\theta_E} \right)}, \quad p^*_H,1 = \frac{2\theta_H - \theta_L}{2 \left( 4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E} \right)}, \quad \text{and} \quad p^*_E,1 = \frac{4\theta_E - 2\theta_H - \frac{\theta_L}{\theta_E} \frac{\theta_M}{\theta_H}}{2 \left( 4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E} \right)}. \]

- After the inferior entry (i.e., \( 1 < \theta_E < \theta_L < \theta_H < 1.5 \)), a pure-strategy Nash equilibrium can be characterized as follows:

- Sellers’ supply:

\[ Q^*_E,1 = \frac{1 + \mu}{2 \left( 4 - \frac{\theta_L}{\theta_E} - \frac{\theta_M}{\theta_E} \right)}, \quad Q^*_L,1 = \left( 2 - \frac{\theta_E}{\theta_L} \right) Q^*_E,1, \quad \text{and} \quad Q^*_H,1 = \left( 4 - \frac{\theta_E}{\theta_L} - \frac{2\theta_L}{\theta_H} \right) Q^*_E,1. \]

- Buyers’ choices:

\[ X^*_L,1 = Y^*_L,1 = \left[ \frac{1}{2 \left( 4 - \frac{\theta_L}{\theta_E} - \frac{\theta_M}{\theta_E} \right)}, \frac{1}{4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E}} \right], \]

\[ X^*_H,1 = Y^*_H,1 = \left[ \frac{1}{4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E}}, \frac{1}{2 \left( 4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E} \right)} \right], \]

and \[ X^*_E,1 = Y^*_E,1 = \left[ \frac{4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E}}{2 \left( 4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E} \right)}, 1 \].

- Prices:

\[ p^*_E,1 = \frac{\theta_E}{2 \left( 4 - \frac{\theta_L}{\theta_E} - \frac{\theta_M}{\theta_E} \right)}, \quad p^*_L,1 = \frac{2\theta_E - \theta_L}{2 \left( 4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E} \right)}, \quad \text{and} \quad p^*_H,1 = \frac{4\theta_E - 2\theta_L - \frac{\theta_L}{\theta_E} \frac{\theta_M}{\theta_H}}{2 \left( 4 - \frac{\theta_L}{\theta_M} - \frac{\theta_M}{\theta_E} \right)}. \]

The proof follows the same argument as shown in Proposition 5’s proof, so we omit it for brevity.

**Proof for Proposition 2**

We prove the proposition for the case of the SPR entry and the IPR entry separately.

**SPR entry.**

Under the SPR entry, the equality of PU sellers’ supply ratios before and after entry (i.e., \( Q^*_H,0/Q^*_H,0 = Q^*_L,0/Q^*_L,0 \)) holds because it follows that \( Q^*_L,0/Q^*_H,0 = 2 - \theta_L/\theta_H = Q^*_H,1/Q^*_E,1 \) by Propositions 4 and 8. To prove a similar equality in revenue ratios (i.e., \( \pi^*_H,1/\pi^*_L,1 = \pi^*_H,0/\pi^*_L,0 \)), we note that

\[ \frac{p^*_H,1}{p^*_L,1} = \frac{\theta_H}{\theta_L}, \quad \frac{Q^*_H,1}{Q^*_L,1} = \frac{\theta_H}{\theta_L}, \quad \frac{Q^*_H,0}{Q^*_L,0} = \frac{p^*_H,0}{p^*_L,0}. \]
This price result combined with the supply result directly imply that \( \pi_{H,1}^*/\pi_{L,1}^* = \pi_{H,0}^*/\pi_{L,0}^* \). This concludes the proof of the SPR entry.

**IPR entry.**
In this case, we aim to show that seller \( \theta_H \)'s supply expands relative to seller \( \theta_L \) (i.e., \( Q_{H,1}^*/Q_{H,0}^* > Q_{L,1}^*/Q_{L,0}^* \)). By substituting the equilibrium supply with their characterizations specified by Propositions 4 and 8, the last inequality is equivalent to:

\[
\frac{Q_{H,0}^*}{Q_{L,0}^*} = 2 - \frac{\theta_L}{\theta_H} < 1 + \frac{1 - \frac{\theta_L}{\theta_H}}{2 - \frac{\theta_L}{\theta_H}} = \frac{Q_{H,1}^*}{Q_{L,1}^*}.
\]

The above inequality is equivalent to \( \theta_E > 0 \) and is, thus, true.

To show the related result regarding revenue ratios (i.e., \( \pi_{H,1,1}/\pi_{L,1,1} > \pi_{H,0,0}/\pi_{L,0,0} \)), we note that

\[
\frac{p_{H,1}^*}{p_{L,1}^*} = \frac{\theta_H}{\theta_L} \cdot \frac{Q_{H,1}^*}{Q_{L,1}^*} > \frac{\theta_H}{\theta_L} \cdot \frac{Q_{H,0}^*}{Q_{L,0}^*} = \frac{p_{H,0}^*}{p_{L,0}^*}.
\]

The expression above, combined with the supply result, directly implies that \( \pi_{H,1,1}/\pi_{L,1,1} > \pi_{H,0,0}/\pi_{L,0,0} \) holds. □

This concludes our proof for the proposition.

**Proof for Proposition 3**
In this proof, we aim to show that seller \( \theta_H \) increases their supply quantity and revenues relative to seller \( \theta_L \) (i.e., \( Q_{H,1}^*/Q_{L,1}^* > Q_{H,0,0}/Q_{L,0,0} \)) after the entry of a PR seller of intermediate-quality (i.e., \( \theta_E \in (\theta_L, \theta_H) \) and \( \alpha = 1 \)).

Following Proposition 8, we can characterize PU sellers’ equilibrium supply post-entry by

\[
Q_{L,1}^* = \frac{1}{2} \cdot \frac{1 + \mu}{4 - \frac{\theta_L}{\theta_E} - \frac{\theta_E}{\theta_H}}, \quad Q_{E,1}^* = \left( 2 - \frac{\theta_L}{\theta_E} \right) Q_{L,1}^*, \quad \text{and} \quad Q_{H,1}^* = \left( 4 - \frac{\theta_L}{\theta_E} - 2 \frac{\theta_E}{\theta_H} \right) Q_{L,1}^*.
\]

By the characterization of \( Q_{H,0}^* \) and \( Q_{L,0}^* \) in Proposition 4, we obtain

\[
\frac{Q_{H,1}^*}{Q_{L,1}^*} = 4 - \frac{\theta_L}{\theta_E} - 2 \frac{\theta_E}{\theta_H} > 2 - \frac{\theta_L}{\theta_H} = \frac{Q_{H,0}^*}{Q_{L,0}^*},
\]

which is equivalent to \( \theta_L/\theta_E + 2\theta_E/\theta_H - \theta_L/\theta_H < 2 \). Note that the left side of the last inequality is convex in \( \theta_E \), and it is easy to verify that the inequality holds when \( \theta_E \downarrow \theta_L \) and \( \theta_E \uparrow \theta_H \). Therefore, the inequality above holds for any \( \theta_E \in (\theta_L, \theta_H) \). This concludes the part of the proposition that is concerned with supply quantities.

Next, we show seller \( \theta_H \)'s revenue relatively increases as compared to the revenue of seller \( \theta_L \) (i.e., \( \pi_{H,1}^*/\pi_{L,1}^* > \pi_{H,0}^*/\pi_{L,0}^* \)) by showing the sufficient condition for prices, \( p_{H,1}^*/p_{L,1}^* > p_{H,0}^*/p_{L,0}^* \). This price ratio inequality holds because it is straightforward to verify that for \( t \in \{0, 1\} \), \( p_{H,t}^*/p_{L,t}^* = \theta_H/\theta_L \cdot Q_{H,t}^*/Q_{L,t}^* \). This concludes our proof.

**D.3. Robustness Checks for Analytical Results**
In this section, we relax some of the assumptions in Appendix D.1 and numerically examine the validity of our analytical results, including localized market stealing and expansion (Observation 1), PU sellers’ supply response and revenue outcomes after marquee entry (Observation 2), and PU sellers’ revenue outcomes in absence of supply flexibility (Proposition 1). In these numerical experiments, the assumptions on \( \alpha \) and \( \mu \) are generalized as follows:
(i') Sensitivity of PU and PR buyers: $\alpha \in [1, 1.5]$ (SPR entry), and $\alpha \in [0.5, 1)$ (IPR entry).

(ii') PR buyers’ mass: $\mu \in [0, 1]$.

(iii’) $\theta_L$, $\theta_H$, $\theta_E$ take values from three scenarios within $[1.1, 1.6]$: $\{1.1, 1.15, 1.2\}$, $\{1.3, 1.35, 1.4\}$, and $\{1.5, 1.55, 1.6\}$, which are referred to as Scenarios 1, 2, and 3, respectively.

Each of the Figures 10 through 14 show, respectively, the regions for (i-iii) numerical ranges where the Observations 1 and 2, as well as Propositions 1, 2, and 3, hold (blue) or do not hold (red), respectively. In what follows, we summarize the main observations from the figures.

Figures 10 and 11 show the regions in which localized market stealing and expansion hold, respectively. Regions where these two localized market effects hold are shown in blue. The top row has values of $\alpha$ ranging from 1 to 1.5 for a superior entrant, while the bottom row has $\alpha$’s value ranging from 0.5 to 1 for an inferior entrant. The three columns indicate the quality values that sellers take as denoted in (iii) above. The plots show that these two effects are quite robust to the relaxation of the parameter assumptions as they hold in most of the extended parametric regimes. They, therefore, suggest that for entrant’s of most qualities and reasonable $\alpha$ and $\mu$ values, we would observe both a localized market stealing and a localized market expansion.
Recall that Observation 2 showed that high-quality sellers expand their supply and revenues relatively more (less) after a superior (inferior) marquee seller enters. Figures 12 and 13 show ranges where supply and revenue effects of Observation 2 hold. The figures indicate that for a superior entrant, the proposition holds for all regions we consider. Seller $\theta_H$’s offering dominates seller $\theta_L$’s products due to better quality regardless of entrant type. This preserves the effect of the SPR entrant leading to seller $\theta_H$’s supply and revenue changes due to entry being better off relative to seller $\theta_L$ in all considered parametric regimes. In contrast, seller $\theta_L$’s quality disadvantage means they cannot be always better off than their high-quality peer under the IPR entry (bottom rows in Figures 12 and 13). Although the IPR entry brings in buyers that benefit seller $\theta_L$, seller $\theta_L$’s supply and revenue advantage arises only when the localized market expansion effect is large enough (i.e., sufficiently small $\alpha$ and sufficiently large $\mu$).
Figure 12. PU sellers’ heterogeneous supply reactions under SPR entry (top) and IPR entry (bottom).

The blue (red) region denotes neighboring PU sellers’ supply expansion (contraction) relative to distant PU sellers.

Figure 13. PU sellers’ heterogeneous revenue changes under SPR entry (top) and IPR entry (bottom).

The blue (red) region denotes neighboring PU sellers’ revenue expansion (contraction) relative to distant PU sellers.
Figure 14 presents how Proposition 1 generalizes under the extended parameter regime. Recall, this proposition showed that if PU sellers cannot adjust their supply after marquee entry, then the PU seller neighboring in quality to the marquee entrant has a lower (relative) revenue. The top row of the figure shows that under an SPR entry, seller $\theta_H$’s revenue becomes worse off than seller $\theta_L$ for high values of $\mu$ (blue region). For large values of $\mu$, the SPR entrant comes with a large (equilibrium) supply, which results in a larger stealing effect on the high-quality PU seller. On the other hand, under the IPR entry (bottom row of the figure), the PR entrant benefits seller $\theta_H$ more than seller $\theta_L$ in most cases (blue region), primarily due to the former’s quality advantage. Refrained from adjusting the supply optimally, seller $\theta_L$ can barely exploit the localized market expansion while curbing the localized market stealing to mitigate its disadvantage relative to seller $\theta_H$.

In sum, the numerical analyses suggest that our theory model propositions generalize well around the assumed parameter ranges, but also importantly highlight regions where we should expect different results. In general, large enough values of $\mu$ and values of $\alpha$ that deviate from 1 (higher than 1 for SPR and lower than 1 for IPR) represent our empirical setting as well as the regime where the propositions hold as is. However, for other regimes, a marquee entry can result in opposite effects than what our analytical propositions have implied.

![Figure 14. PU sellers’ heterogeneous revenue changes without supply reactions under SPR entry (top) and IPR entry (bottom). The blue (red) region denotes neighboring PU sellers’ revenue contraction (expansion) relative to distant PU sellers.](image-url)
Electronic Companion

This companion is organized as follows. In Appendices EC.1 and EC.2, we provide the proofs for Propositions 4 and 5. In Appendix EC.3, we state and prove a series of technical lemmas that were used in the previous proofs.

Appendix EC.1: Proof of Proposition 4

Proof. Note that given two options with adjacent qualities, there is a PU buyer on \( \mathbb{R} \) who is indifferent between the two options. By \( x_1 \), we denote the buyer who is indifferent between the outside option and PU seller \( \theta_L \)'s product. By \( x_2 \), we denote the buyer who is indifferent between PU seller \( \theta_L \)'s product and PU seller \( \theta_H \)'s product. Therefore, \( x_1 \) and \( x_2 \) satisfy:

\[
\theta_L x_1 - p^*_L,1 = 0 \quad \text{and} \quad \theta_H x_2 - p^*_H,1 = \theta_L x_2 - p^*_L,1.
\]

Therefore, PU buyers within \([0, x_1)\) choose the outside option, the PU buyers within \([x_1, x_2)\) choose to transact with PU seller \( \theta_L \), and the remaining PU buyers choose to transact with PU seller \( \theta_H \). Next, by the market clearing condition, we have

\[
Q^*_L,0 = x_2 - x_1 \quad \text{and} \quad Q^*_H,0 = x_3 - x_2.
\]

Combining Equations (EC.1) and (EC.2), we solve for the prices as functions of \( Q^*_L,0 \) and \( Q^*_H,0 \). Lastly, we solve for \( Q^*_L,0 \) and \( Q^*_H,0 \) using the first order conditions, respectively. \( \square \)

Appendix EC.2: Proof of Proposition 5

Proof. We follow two steps to establish the equilibrium characterization. First, we verify that for \( i \in \{L, H, E\} \), the characterizations of \( X^*_i,1 \), \( Y^*_i,1 \), and \( p^*_i,1 \) satisfy Expression (8) (i.e., buyers’ optimal choice) and Expression (9) (i.e., market-clearing condition). In this step, we follow Mussa and Rosen (1978) to characterize PU buyers’ and PR buyers’ choices. Second, we establish the optimality of the characterizations of \( Q^*_i,1 \) for \( i \in \{L, H, E\} \). It is worth mentioning that a seller’s revenues are piece-wise quadratic in its supply given others’ supply (see Figure EC.1). Due to the non-concavity, the first-order condition is no longer sufficient in determining the seller’s optimal supply. Instead, we obtain the optimal supply by comparing the local optima within each quadratic region.

Step 1: Consistency of buyers’ choices and market clearing.

Note that given any two options with adjacent qualities, there is a PU buyer on \( \mathbb{R} \) who is indifferent between the two options. We let \( x_1 \) denote the buyer who is indifferent between the outside option and PU seller \( \theta_L \)'s product, \( x_2 \) denote the buyer who is indifferent between PU seller
\( \theta_L \)'s product and PU seller \( \theta_H \)'s product, and \( x_3 \) denote the buyer who is indifferent between PU seller \( \theta_H \)'s product and the SPR's product. Therefore, \( x_1, x_2, \) and \( x_3 \) satisfy:

\[
\begin{align*}
\theta_L x_1 - p^*_L,1 &= 0, \\
&\theta_H x_2 - p^*_H,1 = \theta_L x_2 - p^*_L,1, \\
&\theta_E x_3 - p^*_E,1 = \theta_H x_3 - p^*_H,1. \\
&\tag{EC.3}
\end{align*}
\]

If \( 0 < x_1 < x_2 < x_3 < 1 \), then it is straightforward to verify that the PU buyers within \([0, x_1]\) choose the outside option, the PU buyers within \([x_1, x_2]\) choose to transact with PU seller \( \theta_L \), the PU buyers within \([x_2, x_3]\) choose to transact with PU seller \( \theta_H \), and the PU buyers within \([x_3, 1]\) choose to transact with the SPR.

Likewise, there are three PR buyers, denoted by \( y_1, y_2, \) and \( y_3 \), who are indifferent between two options with adjacent qualities. In particular, buyer \( y_1 \) is indifferent between the outside option and PU seller \( \theta_L \)'s product, buyer \( y_2 \) is indifferent between PU seller \( \theta_L \)'s product and PU seller \( \theta_H \)'s product, and buyer \( y_3 \) is indifferent between PU seller \( \theta_H \)'s product and the SPR's product. Therefore, \( y_1, y_2, \) and \( y_3 \) satisfy:

\[
\begin{align*}
\theta_L^a y_1 - p^*_L,1 &= 0, \\
\theta_H^a y_2 - p^*_H,1 &= \theta_L^a y_2 - p^*_L,1, \\
&\theta_E^a y_3 - p^*_E,1 = \theta_H^a y_3 - p^*_H,1. \\
&\tag{EC.4}
\end{align*}
\]

If \( 0 < y_1 < y_2 < y_3 < 1 \), then it is straightforward to verify that the PR buyers within \([0, y_1]\) choose the outside option, the PR buyers within \([y_1, y_2]\) choose to transact with PU seller \( \theta_L \), the PR buyers within \([y_2, y_3]\) choose to transact with PU seller \( \theta_H \), and the PR buyers within \([y_3, 1]\) choose to transact with the SPR.

Then, by the market clearing condition, we obtain

\[
\begin{align*}
Q^*_L,1 &= x_2 - x_1 + \mu (y_2 - y_1), \\
Q^*_H,1 &= x_3 - x_2 + \mu (y_3 - y_2), \\
Q^*_E,1 &= 1 - x_3 + \mu (1 - y_3). \\
&\tag{EC.5}
\end{align*}
\]

Combining Equations (EC.3), (EC.4), and (EC.5), we solve for \( x_1, x_2, x_3, y_1, y_2, \) and \( y_3 \), as well as \( p^*_L,1, p^*_H,1, \) and \( p^*_E,1 \), which renders Expressions (18) and (19) in Proposition 5.

In addition, we verify \( 0 < x_1 < x_2 < x_3 < 1 \) under the given characterizations of \( Q^*_L,1, Q^*_H,1, \) and \( Q^*_E,1 \). First, we have \( \tau_{L,0} > \tau_{H,L} > \tau_{E,H} \) by Lemma 1. Note that by Equations (EC.3), (EC.4), and (EC.5), we obtain

\[
\begin{align*}
x_1 &= (1 + \mu - Q^*_L,1 - Q^*_H,1 + Q^*_E,1) (1 + \frac{\tau_{L,0}}{\mu})^{-1}, \\
x_2 &= (1 + \mu - Q^*_H,1 - Q^*_E,1) (1 + \frac{\tau_{H,L}}{\mu})^{-1}, \\
x_3 &= (1 + \mu - Q^*_E,1) (1 + \frac{\tau_{E,H}}{\mu})^{-1}.
\end{align*}
\]

It is easy to verify that above expressions directly imply \( x_1 < x_2 < x_3 \). Then, \( x_1 > 0 \) holds as it is equivalent to \( \frac{7 - 2a_2/a_1 - 2a_1}{8 - 2a_2/a_1 - 2a_1} < 1 \), which is easy to verify to be true. To show \( x_3 < 1 \), we notice that it is equivalent to:

\[
1 - \frac{a_2/a_1}{4 - a_1} > \frac{1}{2} \cdot \frac{1 + \mu}{1 + \mu \tau_{E,H}}.
\]
The left side of the above inequality is greater than \( \frac{2}{3} \) since \( a_1 < 1 \), \( a_2 < 1 \), and \( \frac{a_2}{a_1} < 1 \). It hence suffices to show that the right side is less than \( \frac{2}{3} \). By Lemma 2, we obtain \( \tau_{E,H} > \frac{1}{2} \). Therefore, the right side is less than \( \frac{1 + 3\mu}{2 + \mu} \), which is not greater than \( \frac{2}{3} \). Therefore, we have shown \( x_3 < 1 \).

Lastly, we verify \( 0 < y_1 < y_2 < y_3 < 1 \) under the given characterizations of sellers’ supply. First, by Equations (EC.3) and (EC.4), we obtain \( y_1 = \tau_{L,0}x_1 \), \( y_2 = \tau_{H,L}x_2 \), and \( y_3 = \tau_{E,H}x_3 \). Then, \( y_1 > 0 \) and \( y_3 < 1 \) follow (note that \( \tau_{E,H} < 1 \) by Lemma 1). Next, we show \( y_2 > y_1 \) and \( y_2 < y_3 \) (note that \( \tau_{L,0} < 1 \) and \( \tau_{H,L} > \frac{1}{2} \) by Lemma 2). Then, we have:

\[
y_1 < \frac{1}{1 + \mu} (1 + \mu - Q^*_L,1 - Q^*_H,1 - Q^*_E,1) \quad \text{and} \quad y_2 > \frac{1}{2 + \mu} (1 + \mu - Q^*_H,1 - Q^*_E,1).
\]

To show \( y_2 > y_1 \), it suffices to show \( \frac{1}{2 + \mu} (1 + \mu - Q^*_H,1 - Q^*_E,1) > \frac{1}{1 + \mu} (1 + \mu - Q^*_L,1 - Q^*_H,1 - Q^*_E,1) \). The last inequality holds as it is equivalent to \( \mu > 0 \). For \( y_2 < y_3 \), it is equivalent to:

\[
\frac{\tau_{H,L}}{1 + \mu \tau_{H,L}} \cdot \frac{1 + \mu \tau_{E,H}}{\tau_{E,H}} < 2 - \frac{a_1}{2}, \tag{EC.6}
\]

Note that the left side of the above inequality is less than \( \tau_{H,L}/\tau_{E,H} \) due to \( \tau_{H,L} > \tau_{E,H} \) (Lemma 1), and the right side of the above inequality is greater than \( \frac{3}{2} \). By Lemma 3, we obtain \( \tau_{H,L}/\tau_{E,H} < \sqrt{\frac{3}{2}} < \frac{3}{2} \). Therefore, \( y_2 < y_3 \) holds.

Step 2: Optimality of supply.

We show that \( Q^*_L,1 \) is seller \( i \)'s optimal supply for \( i \in \{L,H,E\} \) given that other sellers’ supply follows Equation (17). Noticeably, sellers’ price functions are characterized based on which buyer type(s) (i.e., PU buyers and/or PR buyers) choose to transact with them. As sellers vary their supply, their buyer types may change (e.g., PU buyers may stop buying from them), which can cause their price functions, as well as their revenue functions, to change. As illustrated by Figure EC.1, sellers’ revenue functions are piece-wise concave.

Optimality of \( Q^*_L,1 \) given \( Q^*_H,1 \) and \( Q^*_E,1 \). As shown in Step 1, in a neighborhood of \( Q^*_L,1 \), PU seller \( \theta_L \)'s price function is equal to \( p^*_{L,1} \) in Equation (19), and its revenue is hence equal to the following quadratic form:

\[
\frac{\theta_L}{1 + \mu \tau_{L,0}} (1 + \mu - Q^*_L,1 - Q^*_H,1 - Q^*_E,1)Q^*_L,1. \tag{EC.6}
\]

It is straightforward to verify that \( Q^*_L,1 \) maximizes Expression (EC.6) using the first-order condition.

Notice that the seller’s profit function is characterized by Expression (EC.6) for any \( Q_L,1 \in (Q^*_L,1,1 + \mu - Q^*_H,1 - Q^*_E,1] \) and for any \( Q_L,1 \in (1 + \mu - Q^*_H,1 - Q^*_E,1, +\infty) \) PU seller \( \theta_L \)'s revenue reduces to 0 (as \( p_{L,1}(Q_L,1, Q^*_H,1, Q^*_E,1) = 0 \)). Hence, PU seller \( \theta_L \) has no incentive to increase its supply from \( Q^*_L,1 \).

Next, we examine PU seller \( \theta_L \)'s incentive to decrease the supply from \( Q^*_L,1 \). As \( Q_L,1 \) decreases, its product’s price increases. Then, fewer buyers consider seller PU \( \theta_L \)'s product more attractive than
the outside option (i.e., $x_1$ and $y_1$ increases). When $Q_{L,1}$ becomes small enough, the characterization of the seller’s demand function changes, because either the PU buyers (i.e., $x_1 \geq x_2$) or the PR buyers (i.e., $y_1 \geq y_2$) stop choosing their products. As a result, the seller’s profit function no longer follows Expression (EC.6). Notice that any $Q_{L,1} < Q^*_{L,1}$ such that Expression (EC.6) holds is dominated by $Q^*_{L,1}$. We only need to show that any $Q_{L,1} < Q^*_{L,1}$ such that Expression (EC.6) does not hold is also dominated by $Q^*_{L,1}$. We claim that as $Q_{L,1}$ decreases, PR buyers stop purchasing from the seller before PU buyers do. That is, when $Q_{L,1}$ decreases to the point where $y_1 = y_2$ just holds, we have $x_1 < x_2$. In particular, since $y_1 = \tau_{L,0}x_1$ and $y_2 = \tau_{H,L}x_2$ (by Equations (EC.3) and (EC.4)) and $\tau_{L,0} > \tau_{H,L}$ (Lemma 1), $y_1 = y_2$ implies $x_1 < x_2$ (and $x_1 = x_2$ implies $y_1 > y_2$). Hence, our claim holds. Next, by $y_1 = y_2$, we solve for:

$$Q_{L,1} = (1 + \mu - Q^*_H - Q^*_E) \left(1 - \frac{\theta_H - \theta_L}{\theta_L} \cdot \frac{\theta^*_L + \mu \theta_L}{\theta^*_H - \theta_L + \mu (\theta_H - \theta_L)} \right),$$

which is the lowest value for $Q_{L,1}$ so that the PU seller’s revenue follows Expression (EC.6). Following the argument similar to Step 1, we can show that PU seller $\theta_L$’s revenue under $Q_{L,1} < Q^*_{L,1}$ can be characterized by the following quadratic form:

$$\pi^L_{L,1}(Q_{L,1}; Q^*_H, Q^*_E) \triangleq \theta_L \left(1 + \mu - Q^*_H - Q^*_E \right) \left(\frac{1 + \mu - Q^*_H - Q^*_E}{1 + \mu \tau_{H,L}} - Q_{L,1} \right) Q_{L,1},$$

which is maximized at

$$Q^*_{L,1} = \frac{1}{2} \cdot \frac{1 + \mu - Q^*_H - Q^*_E}{1 + \mu \tau_{H,L}}.$$
We further note that $Q^i_{L,1} > Q_{L,1}$ is equivalent to:

$$\tau_{L,0}^{-1} + \mu > \frac{1}{2} + \mu \tau_{H,L},$$

which holds because $\tau_{L,0}^{-1} > 1$ and $\tau_{H,L} < 1$. As a result, $\pi^i_{L,1}(Q_{L,1}; Q^*_H, Q^*_{E,1})$ increases in $Q_{L,1}$ within $[0, Q_{L,1}]$, using the concavity of $\pi^i_{L,1}$. Therefore, any $Q_{L,1} \in [0, Q_{L,1}]$ is dominated by $Q^i_{L,1}$.

In sum, $Q^i_{L,1}$ is optimal given $Q^*_H$ and $Q^*_{E,1}$.

Optimality of $Q^*_H$ given $Q^*_{L,1}$ and $Q^*_{E,1}$. As shown in Step 1, in a neighborhood of $Q^*_H$, PU seller $\theta_H$’s price function is consistent with $p_H^*$ in Equation (19), and its revenue is hence equal to:

$$\left(\frac{\theta_{L}}{1 + \mu \tau_{L,0}}(1 + \mu - Q^*_H - Q^*_{E,1}) + \frac{\theta_{H} - \theta_{L}}{1 + \mu \tau_{H,L}}(1 + \mu - Q^*_{E,1}) - \left(\frac{\theta_{L}}{1 + \mu \tau_{L,0}} + \frac{\theta_{H} - \theta_{L}}{1 + \mu \tau_{H,L}}\right)Q^*_H\right)Q^*_H.\tag{EC.7}$$

It is straightforward to verify that $Q^*_H$ maximizes Expression (EC.7) using the first order condition.

First, we show that $Q^*_H$ dominates any supply that is less than it. As $Q^*_H$ increases from $Q^*_H$, we obtain $y_2 = y_3$ (i.e., no PR buyers transact with PU seller $\theta_H$) before $x_2 = x_3$ (i.e., no PU buyers transact with PU seller $\theta_H$).\footnote{Note that $y_2 = \tau_{H,1}x_2$, $y_3 = \tau_{E,H}x_3$, and $\tau_{H,L} > \tau_{E,H}$. Therefore, when $Q^*_H$ reduces to the level where $y_2 = y_3$, $x_2 < x_3$ still holds.} By $y_2 = y_3$, we solve for $Q^*_H$:

$$Q^*_H = \frac{1}{1 + \mu \tau_{E,H} + \mu}(1 + \mu - Q^*_E,1),$$

which is the lowest value for $Q^*_H$ so that the PU seller’s revenue follows Expression (EC.7).

Following a similar argument as in Step 1, we can show that PU seller $\theta_H$’s revenue under $Q^*_H < Q^*_H$ can be characterized by:

$$\pi^i_{H,1}(Q^*_H; Q^*_{L,1}, Q^*_{E,1}) = \left(\frac{\theta_{L}}{1 + \mu \tau_{L,0}}\theta_{H} - \theta_{L} \right) \left(1 + \mu - Q^*_E,1\right) + \frac{\theta_{H} - \theta_{L}}{1 + \mu \tau_{H,L}}(1 + \mu - Q^*_{E,1}) - \left(\frac{\theta_{L}}{1 + \mu \tau_{L,0}} + \frac{\theta_{H} - \theta_{L}}{1 + \mu \tau_{H,L}}\right)Q^*_H,\tag{EC.7}$$

which is maximized at

$$Q^i_{H,1} = \left(\frac{\theta_{L}}{1 + \mu \tau_{L,0}} + \frac{\theta_{H} - \theta_{L}}{1 + \mu \tau_{E,H}}\right) \left(1 + \mu - Q^*_E,1\right) - \frac{\theta_{H} - \theta_{L}}{1 + \mu \tau_{H,L}}Q^*_L,1 .$$

We further note that $Q^i_{H,1} > Q^*_H$ is equivalent to:

$$\left(\frac{\theta_{H} - \theta_{L}}{1 + \mu \tau_{E,H}} + \frac{\theta_{L}}{1 + \mu \tau_{L,0}}\right) \left(1 + \mu - Q^*_E,1\right) \left(1 + \mu - Q^*_L,1\right) - (1/\tau_{E,H} - 1/\tau_{H,L}) \left(\theta_{H} - \frac{\mu \tau_{L,0}}{1 + \mu \tau_{L,0}}\theta_{L}\right) > 0.\tag{EC.8}$$
We let $D(\theta_L, \theta_H, \theta_E, \mu)$ denote the left side of Inequality (EC.8). To show Inequality (EC.8) holds under the given conditions, it suffices to show $D(\theta_L, \theta_H, \theta_E, \mu) > 0$ under $\alpha = 1.5, 1 < \theta_L < \theta_H < \theta_E < 1.5$, and $\mu \in (0.2, 1)$. On the one hand, by bounding $D(\theta_L, \theta_H, \theta_E, \mu)$'s first-order partial derivatives with respect to all its arguments, we can show that it is Lipschitz continuous in $\theta_L, \theta_H, \theta_E$, and $\mu$ with Lipschitz constants 13, 12, 4, and 14, respectively. On the other hand, we numerically search for the minimum of $D(\theta_L, \theta_H, \theta_E, \mu)$ within space

$$\Theta = \left\{(\hat{\theta}_L, \hat{\theta}_H, \hat{\theta}_E, \hat{\mu}) \mid \hat{\theta}_L = 1 + 0.015 \times i_L, \hat{\theta}_L \leq 1.5, i_L \in \mathbb{N} \right\},$$

It turns out that $\min_\Theta D(\theta_L, \theta_H, \theta_E, \mu) = 0.82$. Then, for any $\theta_L, \theta_H, \theta_E$, and $\mu$, we can find $\hat{\theta}_L, \hat{\theta}_H, \hat{\theta}_E$, and $\hat{\mu}$ such that $|\theta_L - \hat{\theta}_L| < 0.015, |\theta_H - \hat{\theta}_H| < 0.016, |\theta_E - \hat{\theta}_E| < 0.05$, and $|\mu - \hat{\mu}| < 0.014$. By Lipshitz continuity, we obtain:

$$|D(\theta_L, \theta_H, \theta_E, \mu) - D(\hat{\theta}_L, \hat{\theta}_H, \hat{\theta}_E, \hat{\mu})| < 13|\theta_L - \hat{\theta}_L| + 12|\theta_H - \hat{\theta}_H| + 4|\theta_E - \hat{\theta}_E| + 14|\mu - \hat{\mu}| < 0.8.$$

Therefore, we have

$$D(\theta_L, \theta_H, \theta_E, \mu) > D(\hat{\theta}_L, \hat{\theta}_H, \hat{\theta}_E, \hat{\mu}) - 0.8 \geq \min_\Theta D(\theta_L, \theta_H, \theta_E, \mu) - 0.8 > 0,$$

which justifies Inequality (EC.8). As a result, $\pi_H^1(Q_{H,1}; Q_{L,1}^*, Q_{E,1}^*)$ increases in $Q_{H,1}$ within $[0, Q_{H,1}]$. Therefore, any $Q_{H,1} \in [0, Q_{H,1}]$ is dominated by $Q_{H,1}^*$. Next, we show that $Q_{H,1}^*$ dominates any supply that is more than it. As $Q_{H,1}$ increases from $Q_{H,1}^*$, it will reach the level where all buyers transact with sellers on the platform (i.e., $Q_{L,1}^* + Q_{H,1}^* + Q_{E,1}^* = 1 + \mu$). We let $\bar{Q}_{H,1} = 1 + \mu - Q_{L,1}^* - Q_{E,1}^*$ denote the level. By using a similar argument as in Step 1, we show that PU seller $\theta_H$’s revenue function can be characterized as follows under $Q_{H,1} > \bar{Q}_{H,1}$:

$$\pi_{H,1}^*(Q_{H,1}; Q_{L,1}^*, Q_{E,1}^*) = \frac{\theta_H - \theta_L}{1 + \mu\tau_{H,L}}(1 + \mu - Q_{H,1} - Q_{E,1})Q_{H,1},$$

which is maximized at

$$Q_{H,1}^* = \frac{1}{2}(1 + \mu - Q_{E,1}^*).$$

We then note that $Q_{H,1}^* < \bar{Q}_{H,1}$ holds because it is equivalent to $a_1 < 2$, where $a_1$ is characterized in Proposition 5. The last inequality immediately follows since $a_1 < 1$. Then, $Q_{H,1}^* < \bar{Q}_{H,1}$ implies that $\pi_{H,1}^*(Q_{H,1}; Q_{L,1}^*, Q_{E,1}^*)$ decreases in $Q_{H,1}$ within $[Q_{H,1}, 1 + \mu - Q_{E,1}^*]$. Also, the PU seller’s revenue remains 0 for $Q_{H,1} > 1 + \mu - Q_{E,1}^*$. Therefore, any $Q_{H,1} \in [\bar{Q}_{H,1}, 1 + \mu - Q_{E,1}^*]$ is dominated by $Q_{H,1}^*$. In sum, $Q_{H,1}^*$ is optimal given $Q_{L,1}^*$ and $Q_{E,1}^*$. e-companion to : Marketplace Expansion through Marquee Seller Adoption
Optimality of $Q_{E,1}^*$ given $Q_{L,1}^*$ and $Q_{H,1}^*$. As shown in Step 1, in a neighborhood of $Q_{E,1}^*$, PU seller $E$’s price function is consistent with $p_{E,1}^*$ in Equation (19), and its revenue is hence equal to:

$$
\left( \frac{\theta_L}{1 + \mu \tau_{L,0}}(1 + \mu - Q_{L,1}^* - Q_{H,1}^*) + \frac{\theta_H - \theta_L}{1 + \mu \tau_{H,L}}(1 + \mu - Q_{H,1}^*) + \frac{\theta_E - \theta_H}{1 + \mu \tau_{E,H}}(1 + \mu) \right) Q_{E,1}^* - \left( \frac{\theta_L}{1 + \mu \tau_{L,0}} + \frac{\theta_H - \theta_L}{1 + \mu \tau_{H,L}} + \frac{\theta_E - \theta_H}{\mu} \right) Q_{E,1}^*.
$$

(EC.9)

It is straightforward to verify that $Q_{E,1}^*$ maximizes Expression (EC.10).

First, we show that $Q_{E,1}^*$ dominates any supply that is less than it. As $Q_{E,1}^*$ decreases from $Q_{E,1}^*$, $x_3 = 1$ (i.e., no PU buyers transact with entrant $\theta_E$) arises before $y_3 = 1$ (i.e., no PR buyers transact with entrant $\theta_E$). By $x_3 = 1$, we solve for:

$$
Q_{E,1}^* = \mu(1 - \tau_{E,H}),
$$

which is the lowest value for $Q_{E,1}^*$ so that Expression (EC.10) holds for the entrant’s revenue. Following a similar argument as in Step 1, the entrant’s revenue under $Q_{E,1} < Q_{E,1}^*$ can be characterized by:

$$
\pi_{E,1}^*(Q_{E,1}; Q_{L,1}^*, Q_{H,1}^*) = \left( \frac{\theta_E^* - \theta_H^*}{1 + \mu \tau_{L,0}}(1 + \mu - Q_{L,1}^* - Q_{H,1}^*) + \frac{\theta_H - \theta_L}{1 + \mu \tau_{H,L}}(1 + \mu - Q_{H,1}^*) \right) Q_{E,1}^* - \left( \frac{\theta_L}{1 + \mu \tau_{L,0}} + \frac{\theta_H - \theta_L}{1 + \mu \tau_{H,L}} + \frac{\theta_E^* - \theta_H^*}{\mu} \right) Q_{E,1}^*.
$$

which is maximized at:

$$
Q_{E,1}^* = \frac{1}{2} \cdot \frac{\theta_E^* - \theta_H^* + \theta_L}{1 + \mu \tau_{L,0}}(1 + \mu - Q_{L,1}^* - Q_{H,1}^*) + \frac{\theta_H - \theta_L}{1 + \mu \tau_{H,L}}(1 + \mu - Q_{H,1}^*)
$$

We further note that $Q_{E,1}^* > Q_{E,1}^*$ is equivalent to:

$$
\frac{\theta_L}{1 + \mu \tau_{L,0}} Q_{L,1}^* + \left( \frac{\theta_L}{1 + \mu \tau_{L,0}} + \frac{\theta_H - \theta_L}{1 + \mu \tau_{H,L}} \right) (Q_{H,1}^* - 1 + \mu - 2 \mu \tau_{E,H}) + \theta_E^* - \theta_H^* - 2(\theta_E - \theta_H) < 0.
$$

We prove the inequality above using the same method as we show in Inequality (EC.8), so we omit the proof for brevity. As a result, $\pi_{E,1}^*(Q_{E,1}; Q_{L,1}^*, Q_{H,1}^*)$ increases in $Q_{E,1}$ within $[0, Q_{E,1}^*]$. Therefore, any $Q_{E,1} \in [0, Q_{H,1}^*]$ is dominated by $Q_{E,1}^*$.

Next, we show that $Q_{E,1}^*$ dominates any supply that is greater than it. As $Q_{E,1}^*$ increases from $Q_{E,1}^*$, it will reach the level where all buyers transact with sellers on the platform (i.e., $Q_{E,1}^* + Q_{H,1}^*$ increases from $Q_{E,1}^*$).

Note that $y_3 = \tau_{E,H} x_3$ and $\tau_{E,H} < 1$. Thus, when $Q_{E,1}^*$ reduces to the level where $x_3 = y_3$, $y_3 < 1$ still holds.

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$Q_{E,1} = 1 + \mu$). We let $\bar{Q}_{E,1} = 1 + \mu - Q_{L,1} - Q_{H,1}$ denote the level. By using a similar argument as in Step 1, we show that entrant $\theta_E$’s revenue can be characterized as follows under $Q_{E,1} > \bar{Q}_{E,1}$:

$$
\pi'^r_{E,1}(Q_{E,1}; Q_{L,1}^*, Q_{H,1}^*) = \left( \frac{\theta_H - \theta_L}{1 + \mu \tau_{H,L}} (1 + \mu - Q_{H,1}^*) + \frac{\theta_E - \theta_H}{1 + \mu \tau_{E,L}} (1 + \mu) \right)
- \left( \frac{\theta_H - \theta_L}{1 + \mu \tau_{H,L}} + \frac{\theta_E - \theta_H}{1 + \mu \tau_{E,L}} \right) Q_{E,1},
$$

which is maximized at:

$$
Q'^r_{E,1} = \frac{1}{2} \cdot \frac{\theta_H - \theta_L}{1 + \mu \tau_{H,L}} (1 + \mu - Q_{H,1}^*) + \frac{\theta_E - \theta_H}{1 + \mu \tau_{E,L}} (1 + \mu).
$$

We then note that $Q'^r_{E,1} < \bar{Q}_{E,1}$ is equivalent to:

$$
1 + \mu - 2(Q_{L,1}^* + Q_{H,1}^*) > -\frac{\theta_H - \theta_L}{1 + \mu \tau_{H,L}} \cdot Q_{H,1}^*.
$$

The inequality above holds because its left side is positive,\footnote{Note that $1 + \mu - 2(Q_{L,1}^* + Q_{H,1}^*) > 0$ is equivalent to $\frac{\theta_H - \theta_L}{\tau_{H,L}} < 2$, which apparently holds. As a result, the entrant’s revenue continues to decrease in $Q_{E,1}$ for $Q_{E,1} > \bar{Q}_{E,1}$. Therefore, any $Q_{E,1} \in [Q_{E,1}, 1 + \mu]$ is dominated by $Q^*_E$.}

We have that $Q'^r_{E,1} < \bar{Q}_{E,1} = 1 + \mu - Q_{H,1}^*$ holds as it is equivalent to $\frac{\theta_H - \theta_L}{\tau_{H,L}} < 2$, which apparently holds. As a result, the entrant’s revenue continues to decrease in $Q_{E,1}$ for $Q_{E,1} > \bar{Q}_{E,1}$. Therefore, any $Q_{E,1} \in [Q^*_E, 1 + \mu]$ is dominated by $Q^*_E$.

In sum, $Q^*_E$ is optimal given $Q_{H,1}$ and $Q_{L,1}$.

\[ \]

### Appendix EC.3: Auxiliary Results

**Proof for Lemma 1**

The first inequality holds as it is equivalent to $\left( \frac{a_2}{a_1} \right)^{\alpha - 1} > 1$, which apparently follows. The second inequality is equivalent to $\left( \frac{a_2}{a_1} \right)^{\alpha - 1} > 1$, which also holds.\[ \]

**Lemma 2.** Suppose $\alpha \in (1, 6]$ and $1 < \theta_1 < \theta_2 < \bar{\theta}$. Then, $\frac{\theta_2 - \theta_1}{\theta_2 - \bar{\theta}} > (\bar{\theta}^{\alpha - 1})^{-1}$.\[ \]
Proof. We let $f_1(\theta_1, \theta_2, \alpha) \triangleq \frac{\partial f_1}{\partial \theta_1}(\theta_1, \theta_2, \alpha)$. First, we show that $\frac{\partial f_1}{\partial \theta_1}(\theta_1, \theta_2, \alpha) \leq 0$ when $\theta_1 < \theta_2$. In particular, $\frac{\partial f_1}{\partial \theta_1}(\theta_2, \theta_1, \alpha)$ has the same sign as $h_1(\theta_1; \theta_2, \alpha) \triangleq -\theta_2^\alpha + \theta_1^\alpha + \alpha \theta_1^{\alpha-1}(\theta_2 - \theta_1)$. Note that $h_1(\theta_2; \theta_2, \alpha) = 0$ and $\frac{\partial h_1}{\partial \theta_1}(\theta_1; \theta_2, \alpha) = \alpha(1-\alpha)\theta_1^{\alpha-2}(\theta_2 - \theta_1) > 0$ under $\theta_1 < \theta_2$. Thus, it follows that $h_1(\theta_1; \theta_2, \alpha) < 0$, which renders $\frac{\partial f_1}{\partial \theta_1}(\theta_1, \theta_2, \alpha) \leq 0$. Then, we notice that $f_1(\theta_1, \theta_2, \alpha) \geq f_1(\theta_2, \theta_2, \alpha) = \frac{1}{\alpha \theta_2^{\alpha-1}}$, which decreases in $\alpha$ and $\theta_2$. Note that $\alpha \leq \alpha$ and $\theta_2 < \bar{\theta}$. Therefore, we have $f_1(\theta_1, \theta_2, \alpha) > (\bar{\alpha} \theta_2^{\alpha-1})^{-1}$.

□

Lemma 3. Suppose $\alpha \in (1, \bar{\alpha})$ and $1 < \theta_1 < \theta_2 < \theta_3 < \bar{\theta}$. Then, $\frac{\partial^2 f_1}{\partial \theta_1^2} \frac{\partial^2 f_1}{\partial \theta_2^2} \frac{\partial f_1}{\partial \theta_1} \frac{\partial f_1}{\partial \theta_2} < \bar{\theta}^{-1}$.

Proof. In the proof of Lemma 2, we have shown that $\frac{\partial^2 f_1}{\partial \theta_1^2} \frac{\partial^2 f_1}{\partial \theta_3^2} \frac{\partial f_1}{\partial \theta_1} \frac{\partial f_1}{\partial \theta_3} < \bar{\theta}^{-1}$. Next, we show that $\frac{\partial^2 f_2}{\partial \theta_2^2} \frac{\partial^2 f_1}{\partial \theta_2^2} \frac{\partial f_2}{\partial \theta_2} \frac{\partial f_1}{\partial \theta_2} < \bar{\theta}^{-1}$. We let $f_2(\theta_2, \theta_3, \alpha) \triangleq \frac{\partial f_1}{\partial \theta_1}(\theta_2, \theta_3, \alpha)$, and we can show that $\frac{\partial^2 f_2}{\partial \theta_2^2} \frac{\partial^2 f_1}{\partial \theta_3^2} \frac{\partial f_2}{\partial \theta_2} \frac{\partial f_1}{\partial \theta_3} = \alpha(1-\alpha)\theta_2^{\alpha-2}(\theta_3 - \theta_2) < 0$ when $\theta_3 > \theta_2$. Therefore, $h_2(\theta_3; \theta_2, \alpha) > 0$ for $\theta_3 > \theta_2$, which renders $\frac{\partial^2 f_2}{\partial \theta_2^2} \frac{\partial^2 f_1}{\partial \theta_2^2} \frac{\partial f_2}{\partial \theta_2} \frac{\partial f_1}{\partial \theta_2} < \bar{\theta}^{-1}$.

Next, it suffices to show
\[
\theta_2 - 1 \cdot \theta^\alpha - \theta_2^\alpha = \frac{\theta_2 - 1}{\theta - \theta_2} \cdot \left( \frac{\theta^\alpha - 1}{\theta^2} - 1 \right) < \bar{\theta}^{-1}.
\]
We can show that $\frac{\partial}{\partial \alpha} \left( \frac{\theta^\alpha - 1}{\theta^2} - 1 \right) > 0$.\(^{38}\) Therefore, we have
\[
\frac{\theta_2 - 1}{\theta - \theta_2} \cdot \left( \frac{\theta^\alpha - 1}{\theta^2} - 1 \right) < \frac{\theta_2 - 1}{\theta - \theta_2} \cdot \left( \frac{\theta^\alpha - 1}{\theta^2} - 1 \right) < \frac{\theta_2 - 1}{\theta - \theta_2} \cdot \bar{\theta}^{-1}.
\]
Notice that $\frac{\theta^\alpha - 1}{\theta^2} - 1$ decreases in $\theta_2$ (shown earlier in the proof) and $\frac{\theta^\alpha - 1}{\theta^2} - 1$ increases in $\theta_2$ (by the proof of Lemma 2). Therefore, the right side of the inequality is less than $\bar{\theta}^{-1}$, which completes the proof.

□

Lemma 4. Suppose $1 < \theta_1 < \theta_2 < \bar{\theta}$, $\alpha \in (\alpha, 1)$ where $\alpha > 0$. Then, $\frac{\partial^2 f_1}{\partial \theta_2^2} \frac{\partial^2 f_2}{\partial \theta_2^2} < \frac{1}{\alpha \theta_2^{\alpha-1}}$.

Proof. We let $f_2(\theta_1, \theta_2, \alpha) \triangleq \frac{\partial^2 f_1}{\partial \theta_2^2}(\theta_1, \theta_2, \alpha)$.

First, we show that $\frac{\partial^2 f_1}{\partial \theta_1^2}(\theta_1, \theta_2, \alpha) > 0$. Note that $\frac{\partial^2 f_1}{\partial \theta_1^2}(\theta_1, \theta_2, \alpha)$ has the same sign as $g_4(\theta_1; \theta_2, \alpha) \triangleq -\theta_2^\alpha + \theta_1^\alpha + \alpha \theta_1^{\alpha-1}(\theta_2 - \theta_1)$. Because $g_4(\theta_2; \theta_2, \alpha) = 0$ and $\frac{\partial g_4}{\partial \theta_1}(\theta_1; \theta_2, \alpha) = \alpha(1-\alpha)\theta_1^{\alpha-2}(1-\theta_2/\theta_1) < 0$, we have $g_4(\theta_1; \theta_2, \alpha) > 0$ and $\frac{\partial^2 f_1}{\partial \theta_1^2}(\theta_1, \theta_2, \alpha) > 0$.

Second, we show that $\frac{\partial^2 f_1}{\partial \theta_2^2}(\theta_1, \theta_2, \alpha) > 0$. Note that $\frac{\partial^2 f_1}{\partial \theta_2^2}(\theta_1, \theta_2, \alpha)$ has the same sign as $h_4(\theta_2; \theta_1, \alpha) \triangleq \theta_2^\alpha - \theta_1^\alpha + \alpha \theta_1^{\alpha-1}(\theta_2 - \theta_1)^{-1}$. Because $h_4(\theta_2; \theta_1, \alpha) = 0$ and $\frac{\partial h_4}{\partial \theta_2}(\theta_2; \theta_1, \alpha) = \alpha(1-\alpha)\theta_1^{\alpha-2}(1-\theta_2/\theta_1) > 0$, we have $h_4(\theta_2; \theta_1, \alpha) > 0$ and $\frac{\partial^2 f_1}{\partial \theta_2^2}(\theta_1, \theta_2, \alpha) > 0$.

Therefore, we have
\[
f_4(\theta_1, \theta_2, \alpha) < \frac{\bar{\theta} - \theta_1}{\theta^\alpha - \theta_1} < \frac{1}{\alpha \theta_2^{\alpha-1}} < \frac{1}{\alpha \theta_2^{\alpha-1}},
\]
which completes the proof.

\(^{38}\) Note that the inequality is equivalent to $\frac{\theta^\alpha \log \bar{\theta}}{\theta^\alpha - 1} > \frac{\theta_2^\alpha \log \bar{\theta}}{\theta_2^\alpha - 1}$. The last inequality holds because its right side increases in $\theta_2$ and $\theta_2 < \bar{\theta}$.