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The Effect of Online Shopping Platform Strategies on Search, Display, and Membership Revenues☆

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Abstract

Most online shopping platform firms generate revenue from three sources: pay-per-click search advertising, pay-per-impression display advertising, and membership fees. The strategies that influence these revenue sources typically are studied individually, rather than in a holistic fashion. In response, this study uses time-series data with 18 million buyers and sellers from 2010 to 2011 and undertakes a quasi-experiment to analyze how the distinct effects of buyer- and seller-side strategies on revenues (1) vary across all three revenue sources and (2) depend differentially on a platform's upmarket repositioning strategy. The results show that buyers that purchase through direct traffic (e.g., typing in the site address) yield more display advertising and membership fee revenues than those gained through organic traffic (e.g., landing from a search engine). Engagement strategies that appeal to established sellers (i.e., value-added services) yield more search advertising and membership revenue than those that appeal to new sellers (i.e., social forums). An upmarket repositioning strategy (i.e., eliminating low quality sellers) enhances the revenue effects of buyer traffic generation and seller engagement strategies. Post hoc analyses suggest that a 1% increase in direct traffic generates an additional $151,506 in display advertising revenue after (vs. before) the repositioning.
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Keywords: Search advertising; Display advertising; Membership fee; Two-sided markets; Online shopping platforms; Upmarket repositioning

The popularity of online shopping platforms, such as eBay, Rakuten, and Alibaba, is growing exponentially. According to an industry analysis, these two-sided platform companies "receive valuations two to four times higher . . . than companies with other business models" and are outperforming competitors in both their growth rates and profit margins (Libert, Wind, and Fenley 2014). Firms that participate on these shopping platforms often rely on a business model in which their services are available for free to buyers, but they extract profits from sellers. Accordingly, online platform firms collect revenues from sellers in three main ways: pay-per-click search advertising, pay-per-impression display advertising, and membership fees (Edelman 2014). To increase their revenue from these sources, the platform firms employ traffic generation strategies to bring buyers to the site, as well as seller engagement strategies to attract, enhance, and maintain sellers in the shopping journey. Yet extant research typically takes a piecemeal approach and addresses one revenue source at a time (Fang et al. 2015; Tucker and Zhang 2010). Instead, the primary objective of this article is to *determine the relative revenue effects of buyer- and seller-side strategies across all three platform revenue sources simultaneously*.

Managers are interested in the revenue effects of specific, *micro-level* (i.e., buyer- and seller-side) strategies, but platform firms also can adjust their *macro-level* strategy, which has performance implications for both buyers and sellers on those platforms. In particular, as online platform firms mature, they often implement an upmarket repositioning strategy, similar to those that are prevalent in brick-and-mortar channels (Slywotzky et al. 2000). In this transition, the platform seeks to improve the quality of the products available on its site and thereby raise the overall level of reliability of the platform. For example, in

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an anti-counterfeiting campaign, eBay "banished tens of thousands of sellers from its auction marketplace who did not meet new, elevated standards," after realizing that the loss of buyers' trust would cause severe damage to its future revenue growth and potentially provoke costly lawsuits (The New York Times 2007). Because failing to foster trustworthiness creates "negative externalities" and "threaten[s] your core value proposition to your most valuable customers" (Halaburda 2010), it is critical to understand how macro-level upmarket repositioning strategies by a platform affect existing buyer- and seller-side strategies. Thus, a second objective of this research is *to understand how a macro-level, upmarket repositioning strategy influences the effects of buyer- and seller-side strategies on all three revenue sources*.

To test our overall conceptual framework, we analyze unique time series data from a global business-to-business (B2B) online platform company that serves 18 million buyers and sellers from more than 190 countries. It showcases a wide array of products, from raw materials to finished goods, in more than 40 industry categories. This data set offers unique research opportunities. First, the information about multiple revenue sources provides a comprehensive picture of the platform's business model. Second, the data describe a wide array of micro-level strategies, on both buyer and seller sides, so we can test the relative revenue effects of the strategies across revenue sources. Third, the data capture a quasi-experiment, involving upmarket repositioning, so we can observe how the revenue effects of various micro-level strategies changed, from before to after the repositioning. We use a vector autoregression model with exogenous variables (VARX), which can account for the dynamic relationship between firm strategies and revenue responses (e.g., carryover effects), as well as the endogeneity of the variables and simultaneous equation models.

With this approach, we contribute to extant literature in three ways. First, we generate a parsimonious conceptual model to synthesize the empirical findings and capture how the revenue effects of buyer- and seller-side strategies vary across different platform revenue sources, which helps advance theory in this relatively new channel context. To do so, we explicitly examine the *revenues generated by different buyer traffic generation strategies across all three platform revenue sources*. For example, buyers that access the platform as organic traffic generate more search advertising revenue than those that represent direct traffic, because they search to collect information. In contrast, buyers obtained through direct traffic generate more display advertising revenue than organic or referral traffic, because they are more receptive to advertising.

Second, we offer a concise, theoretical explanation for the revenues generated by different seller-side strategies. The duration of sellers' experience on the platform influences *the revenue effects of seller engagement strategies across all three online platform revenue sources*. For example, a marketing initiative appealing to new sellers (social forums) yields more display advertising revenue than one appealing to established sellers (value-added services), because it is more valuable for new sellers to generate awareness of their offerings through display advertisements. We also find that a marketing initiative appealing to established sellers (value-added services) leads into more search advertising and membership fee revenue than one appealing to new sellers (social forums).

Third, we use a quasi-experiment, premised on the platform's macro-level, upmarket repositioning, which was designed to raise the reliability of the entire platform. This shift had system-wide effects on both traffic generation among buyers and engagement among sellers, such that the *upmarket repositioning strategy enhances the positive effects of buyer- and seller-side strategies on revenue sources*. Attracting more buyers or enhancing sellers' engagement pays off more as the firm moves upmarket, though at the expense of a reduction in the number of buyers and sellers, at least initially.

Understanding Online Shopping Platform Firms' Business Models

Online shopping platform firms use three revenue models to capitalize on the transactions between buyers and sellers that take place through their site (Lambrecht et al. 2014; Mathmann et al. 2017; Watson et al. 2015): revenue from platform-based search advertising, revenue from platform-based display advertising, and revenue from membership fees. Because successful revenue generation depends on platforms' ability to pair buyers and sellers, they often employ both buyer- and seller-side strategies to increase the number of revenue-generating interactions.

To explain how buyer- and seller-side strategies influence revenues, we review online platform business model literature (Table 1) and identify four key limitations. First, extant studies consider platform revenue sources independently (Fang et al. 2015; Tucker and Zhang 2010) or measure revenue at an aggregate level (Grewal, Chakravarty, and Saini 2010; Zhang et al. 2012). Tucker and Zhang (2010) focus solely on display advertising; Fang et al. (2015) narrow their research scope to search advertising revenue. Second, prior research into buyer-side strategies often ignores the various sources of buyer traffic and the potentially distinct impacts of each traffic source on multiple revenue streams (Zhang et al. 2012). Third, most studies do not consider how seller-side strategies can yield more platform revenues. For example, Grewal, Chakravarty, and Saini (2010) discuss the importance of building seller social communities, to encourage other sellers to participate, but they do not address any other seller-side marketing initiatives. Fourth, extant research do not describe the actual application of an upmarket repositioning strategy in an online shopping platforms context. As we note in the last row of Table 1, our research thus *provides a more comprehensive view of online platform success by integrating both buyer- and seller-side strategies to understand their relative effects on all three revenue sources*.

Platform Revenue Sources

Revenue from search advertising

Platforms earn search advertising revenues by hosting a keyword bidding system, in which sellers list products on the platform's website, and buyers search for items they need. Search advertising relies on a pay-per-click model, so there is

Table 1
Literature review of buyer- and seller-side strategies on online platform revenue sources.

Authors	Research context	Level of analysis	Online platform revenue sources			Buyer-side strategies	Seller-side strategies	Findings
			Pay-per-click	Pay-per-impression	Fixed fee			
Edelman (2014)	Theoretical discussion of launching an online platform	Platform	√ (pay-as-you-go)			Building social communities of buyers, attracting marquee users	N/A	Platforms can improve their odds of success by leveraging existing users, building small social groups, attracting marquee users, and ensuring compatibility with legacy systems.
Fang et al. (2015)	Business-to-business platform supporting various industries	Platform	√ (search advertising)			New vs. existing buyers	New vs. existing sellers	After buyers and sellers on the platform have adapted to the new search advertising service (mature stage), new buyers click on more search advertisements than existing buyers.
Grewal, Chakravarty, and Saini (2010)	Survey of 107 executives from business-to-business electronic markets	Platform	Aggregated overall performance			N/A	Social community	Community building improves electronic market performance, and its effectiveness is suppressed by dynamic rather than static price-making mechanisms.
Hagiu (2014)	Theoretical discussion of multisided platforms based on case studies	Platform	√ (royalty)		√ (fixed fee)	N/A	N/A	Pricing structure and governance rules determine the profitability of multi-sided platforms.
Lambrecht et al. (2014)	Review of online firm's revenue models	Platform, Individual	√ (search advertising)	√ (display advertising)		N/A	N/A	Buyers use an online firm's service at no charge, in return for their time and information. Online firms collect revenue by brokering buyer information or listing advertising. There are some trade-offs that the firm faces with different revenue models.
Tucker and Zhang (2010)	Field experiment from a business-to-business website	Individual		√ (display advertising)		Advertising the number of sellers on the platform	Advertising the number of buyers on the platform	Providing information about the number of buyers, the number of sellers, and the presence of a larger number of sellers reduces further seller listings. This deterrence effect is weakened when only the number of sellers is presented. Similarly, publicizing a large buyer base attracts new listings when it is displayed together with the number of sellers.
Zhang et al. (2012)	Weekly data from a major consumer-to-consumer website in Europe	Platform	Aggregated overall performance			Buyer acquisition and buyer retention	Seller acquisition and seller retention	Due to sellers' strong network effects on content consumers (buyers) and other contributors, seller acquisition contributes the most to cumulative financial value, as well as network effects, followed by buyer acquisition, seller retention, and finally buyer retention.
This study	Business-to-business electronic platform	Platform	√ (search advertising)	√ (display advertising)	√ (membership fee)	Direct, referral, organic traffic	Value-added services, social forums	Buyers that purchase through direct traffic (e.g., typing in the site address) yield more display advertising and membership fee revenues than those gained through organic traffic (e.g., landing from a search engine). Engagement strategies that appeal to established sellers (i.e., value-added services) yield more search advertising and membership revenue than those that appeal to new sellers (i.e., social forums).

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no upfront fee. Sellers bid on keyword phrases, and the platform charges sellers only when buyers click the product listing generated by the keyword phrases they have entered (Fang et al. 2015). Examples of platform firms that use this model include eBay's AdCommerc, Amazon's Headline Search Ads, and Google's AdWords. Empirical research pertaining to search advertising mainly investigates search ad placement (Agarwal, Hosanagar, and Smith 2011) and buyers' click behavior (e.g., conversion rates, click-through rates) at a keyword level (Ghose and Yang 2009; Rutz, Bucklin, and Sonnier 2012), without accounting for other revenue models at the same time.

Revenue from display advertising

Platform firms often use a display advertising model too. It operates on a pay-per-impression approach, such that sellers pay a predetermined, fixed amount to ensure a specified number of advertising exposures, whether as pop-up, floating, banner, or text advertising. Therefore, display advertising revenue is a direct function of the number of sellers that participate. The price of display advertising varies according to multiple factors, such as the time of day/week the advertising appears and the location of the websites. The price is set for a specific period of time and adjusted according to "performance" (i.e., buyer behaviors or clicks). Examples include TMall's Zuanzhan, Amazon's Product Display Ads, and Google's Display Network. Prior studies note that display advertising exposures can affect advertising recall (Drèze and Hussherr 2003), obtrusiveness (Goldfarb and Tucker 2011), visitation (Hoban and Bucklin 2015), and Internet purchase decisions (Manchanda et al. 2006).

Revenue from membership fees

In combination with search and display advertising, many online platform firms earn revenue from the membership fees they charge sellers for subscription access for a given period of time. Sellers usually can use basic services at no cost but must pay a membership fee to obtain upgrades and richer usage functionality, which constitutes a freemium model, as illustrated by Amazon's Professional Selling Plan or eHarmony's TotalConnect Plans. Although this model is "a more sustainable source of revenue than the advertising model prevalent among online firms. . ., freemium is still poorly understood" (Kumar 2014, p. 28). In our study context, member sellers may feature an unlimited number of items on the platform site; sellers that do not pay the membership fee may list only a limited number. Membership fees and freemium models are prevalent in practice, yet research in this area is relatively limited (Lambrecht et al. 2014).

As an illustration, we use Amazon's third-party seller Linenspa as an example of how sellers contribute to all three online platform revenue sources. This mattress company employs both display and search ads on Amazon, which has helped it double its average daily sales for promoted items (Alfonso 2017); as a result, Amazon also earns higher revenues. As a premium member, Linenspa pays Amazon's membership fee, along with paying for its display and search ads, thus providing all three sources of revenue.

Micro-Level Strategy: Buyer Traffic Generation Strategies

Inbound traffic to a platform's website consists of three major categories: *direct, referral,* and *organic traffic*. Buyers obtained through these traffic types differ in their level of familiarity with or knowledge about the platform, perceived risk, and trust in sellers and the platform (Li and Kannan 2014; Pauwels et al. 2016; Rutz, Trusov, and Bucklin 2011). Understanding the underlying processes that characterize different types of buyer traffic is critical. At one end of the continuum, *direct traffic* consists of buyers who arrive at the site directly by typing in the site address or clicking a bookmark they have saved. If a customer directly types in "Orbitz.com" on a browser to start the process of booking a flight to Seattle, that customer represents direct traffic. In this "entirely customer-initiated channel" (Li and Kannan 2014, p. 42), buyers may be repeat visitors, with some awareness of the platform, so they likely exhibit high familiarity but low perceived risk with sellers and the platform. At the other end of the continuum is *organic traffic*, or buyers that search using non-paid, external search engines (e.g., Google, Bing, Baidu). Most of these buyers likely are new to or unfamiliar with the platform site, with little prior knowledge of its brands and sellers, so they may perceive higher uncertainty and lower familiarity. An instance of organic traffic might arise if a customer searches for flight deals to Seattle on Google, then clicks on a link to Orbitz.com from among the search results. In the middle, *referral traffic* consists of buyers who search for products or sellers on external, cooperative, referral websites (e.g., expert blogs, partner sites, news sites, posts on social media). They have collected information about the platform from a third party but are still new to it, so they may express median levels of platform familiarity. For example, a customer might find that a colleague has posted on Facebook about getting a good deal on a flight to Seattle, then click on a link within that post that leads to Orbitz.

Micro-Level Strategy: Seller Engagement Strategies

An online shopping platform can adopt two general seller-side strategies to enhance its value to sellers and thus increase platform revenue. First, it can offer sellers *value-added services*, including tools that provide access to buyer information or accounting, stock management, consumer resource management, and predictive analytics services. Because these tools help sellers identify market needs, optimize their selling solutions, and streamline listings, this strategy is especially valuable for *established sellers*, whose primary goal is to target buyers better. For example, eBay's Selling Manager allows sellers to "quickly create and manage listings, track sales status, and perform post-sales tasks" (eBay 2015).

Second, the platform can provide *social forums* in which individual sellers share business ideas and current issues. If sellers perceive the marketplace as not just a money-making endeavor but a community, they are more likely to engage with the platform. Such community-building services "represent the market maker's attempt to create embedded social relationships that help mitigate the risks associated with opportunistic behaviors by market participants" (Grewal, Chakravarty, and Saini 2010,

p. 49). Because this initiative allows sellers to "test the waters" on the platform, it should be especially appealing to *new sellers* that are less familiar with the marketplace and seek help from peer or veteran sellers. Examples of this tool include Amazon's Help for New Sellers, Etsy's Community Forums, and Storenvy's Community.

Macro-Level Strategy: Upmarket Repositioning Strategy

Thus far, we have focused on understanding the micro-level strategies that platform firms employ, but it is also important to understand a platform's macro-level strategy that might enable it to leverage the micro-level strategies. Specifically, platform firms seek to address the trade-off they face as they grow, between the quantity and quality of sellers. In early stages, platforms focus on increasing their market share, often with little regard to the quality of the participants. As it matures, the platform recognizes that its success is "not solely determined by the number of members on its respective sides and the number of interactions they engage in, but also by their quality" (Hagiu 2014, p. 77). In response, it might adopt various approaches, such as rating and feedback mechanisms or rewards for high-quality users (Lambrecht et al. 2014); we focus on efforts to eliminate low quality sellers, or an *upmarket repositioning strategy*, which can have system-wide effects on the platform's micro-level strategies. Many well-known firms, in both online and brick-and-mortar channels, already have made such transitions (Table 2), including eBay (The New York Times 2007), Alibaba (Bloomberg 2014; CNN 2015), Bal Harbour Shops (Fortune 2014), and Nintendo (Hagiu 2014).

Effect of Buyer- and Seller-Side Strategies on Platform Revenue Sources

In this section, we offer rationales for our predictions about (1) which buyer traffic generation and seller engagement strategies generate the most search advertising, display advertising, and membership fee revenues and (2) how the revenue effects of these buyer- and seller-side strategies at a micro-level may depend on the platform's macro-level strategy. As outlined in Fig. 1, we first investigate the relative revenue effects of buyer traffic generation and seller engagement strategies across different platform revenue sources in the absence of an upmarket repositioning strategy, then test how these effects vary after the repositioning strategy.

Effect of Buyer Traffic Generation Strategies on Platform Revenue Sources

Empirical studies of the various types of buyer inbound traffic reveal their distinct effects for generating online marketing revenues (Li and Kannan 2014). We focus on a granular level and distinguish revenue from search advertising, revenue from display advertising, and revenue from membership fees (Fig. 1). We use three rationales to reach our predictions: (1) Buyers obtained from organic traffic search more, (2) direct traffic buyers are more receptive to display ads, and (3) direct traffic buyers complete more sales. From browsing and accessing a website to making purchase decisions, all online marketplace activity, by nature, requires buyers to appraise the risk and trustworthiness of an exchange partner (Schlosser, White, and Lloyd 2006).

Organic traffic and search

Sellers pay the platform when buyers click on search advertisements in the course of their search for merchandise on the platform. The platform can increase search advertising revenue if buyers search more for product information and click on the resulting advertisements. Relative to other traffic sources, buyers from organic traffic tend to be new to the site and thereby express lower familiarity but greater perceived risk related to the seller or product quality, so they search for information and click on more product listings. Buyers with a higher (direct traffic) or medium (referral traffic) level of familiarity instead spend less effort searching, because they have some prior information about the platform and its sellers. Because buyers that arrive as organic traffic seek to gather information through their own queries and search results, they generate more search advertising revenue, in line with the argument that "attracting new buyers to participate in search advertising should have a greater effect on their use of search information (i.e., click rate) than attracting existing buyers" (Fang et al. 2015, p. 412). Thus,

H_1. Organic traffic yields more search advertising revenue than (a) referral traffic and (b) direct traffic.

Direct traffic and ad receptivity

Sellers pay a predetermined, fixed amount for impressions through display advertising. To increase its display advertising revenue, the platform needs to signal to sellers that buyers accept its advertising cues. Buyers with higher familiarity with and knowledge of the platform, such as those who arrive as direct traffic, are more likely to be receptive to display advertisements, relative to other forms of buyer traffic, because these repeat visitors already should be aware of some sellers and products on the platform. Consistent with our argument, extant research shows that for returning customers, "ads may serve as a reminder to complete a transaction" (Hoban and Bucklin 2015, p. 5). Buyers with some prior purchase history on the site also may be more responsive and exhibit higher purchase probabilities than new buyers, because display advertising "acts as reminder tools and/or brand builders for current customers" (Manchanda et al. 2006, p. 102). Organic and referral traffic buyers are likely to perceive greater uncertainty with platform-generated advertising, because they tend to be less aware of the site. Thus,

H_2. Direct traffic yields more display advertising revenue than (a) referral traffic and (b) organic traffic.

Direct traffic and more sales

The structure of online shopping platforms creates a situation in which revenues from sellers coincide with revenues from buyers. For example, membership fee revenues likely increase when sellers expect buyers to complete more sales transactions. That is, sellers may pay membership fees in advance to gain access to additional platform features, because they anticipate

Table 2
Examples of upmarket repositioning strategies in platform marketplaces.

Company	Industry	Motivation and description of upmarket repositioning strategy	Source
eBay	Online auction	In January 2007, eBay announced new efforts to ban the sales of knockoffs and also enhanced its feedback system to provide buyers and sellers more information about each other. These new anticounterfeiting measures meant that eBay repositioned itself to a higher-end marketplace, in which buyers perceive more trust and safety. The implementation of the new measures was a reaction to (1) a huge drop in active users on the site, which was a sign that members found the website insufficiently safe, and (2) Tiffany & Co.'s lawsuit alleging trademark infringement. Since introducing its new anti-counterfeiting measures, eBay has reported "a 60% decline in the number of complaints from luxury goods makers that counterfeits of their products are being sold on the site" but realized that "not every seller loves it.¨	The New York Times (2007)
Alibaba	Online auction	Since 2010, Alibaba has actively cracked down on the sale of knockoffs online. For example, the company has collaborated with law enforcement on intellectual property infringement cases, conducted periodic checks to find counterfeit products, and required sellers to make deposits with Alibaba to ensure the authenticity of the products. The motivation behind this anti-counterfeit policy includes its U.S. initial public offering and multiple lawsuits alleging that Alibaba knowingly profits from the sale of fake goods on its platforms. It is still in the process of regaining trust from buyers.	Bloomberg (2014); CNN (2015)
Bal harbour shops	Offline retailing	While traditional shopping malls have struggled over the past years, some malls have transformed themselves to be perceived as more upscale by adding higher quality dining places and attracting hot new retailers. For example, Bal Harbour Shops in Florida is almost a half century old, but it has continued to remodel to target much higher-end markets. It has added higher-end restaurants and growing names in luxury sectors. As a result, it has been listed as the top U.S. mall in sales per square foot ($3,010).	Fortune (2014)
Nintendo	Video game console	In the early 1980s, console makers failed to maintain tight restrictions on unauthorized games, allowing opportunistic, low quality developers to take advantage of the popularity of video consoles. Because it was nearly impossible to collect information on game quality at the time, the video game console industry nearly collapsed. Learning from the past, Nintendo implemented very strict rules when it released the second version of the Nintendo Entertainment System console. In particular, it carefully reviewed games programmed by individual game developers and restricted the number of games per year. As a result, Nintendo was able to secure its profits, and this version of the console became one of Nintendo's greatest successes.	Hagiu (2014)

higher sales. Direct traffic is empirically associated with the most purchases, relative to referral or organic traffic (Li and Kannan 2014), because these buyers are likely more experienced and knowledgeable about the platform's purchase process (e.g., saved payment information and shipping address), as well as the sellers and brands on the platform. Buyers obtained through organic or referral traffic instead perceive more uncertainty and risk in the seller's quality, so they may be less likely to complete an actual transaction. Formally,

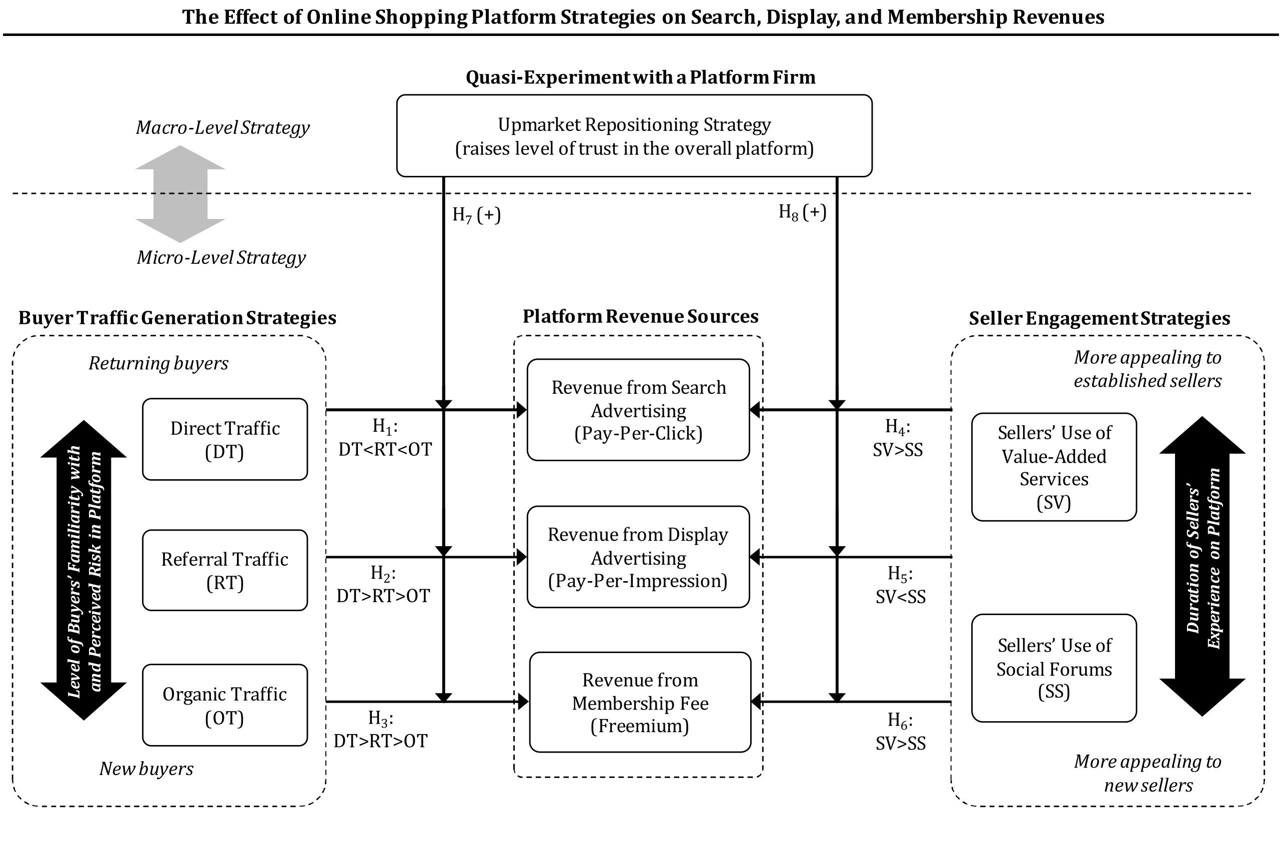
H$_3$. Direct traffic yields more membership fee revenues than (a) referral traffic and (b) organic traffic.

Effect of Seller Engagement Strategies on Platform Revenue Sources

Depending on the duration of a seller's experience on the platform, it may have different marketing priorities, such that it prefers certain marketing initiatives by the platform. In positing that the duration of sellers' experience on the platform determines the relative revenue effect of seller engagement strategies, we predict that sellers' use of value-added services (more appealing to established sellers) leads to more search advertising and membership revenues than their use of social forums (more appealing to new sellers) but generates less display advertising revenue. We rely on the following rationales: (1) Established sellers can better target buyers using search advertising, (2) new sellers need to generate awareness, and (3) established sellers are more likely to expand their product assortments.

Established sellers target buyers using search advertising

Search advertising revenue is a function of buyers' clicks, which depend on sellers' bidding behavior and keyword choices (Fang et al. 2015). In addition, search advertising is more appealing to sellers that want to manage specific keyword phrases precisely to ensure maximum clicks. Established sellers value the ability to manage their keywords efficiently to target buyers, post products that are more relevant to buyers, and assess their post-sales performance metrics to find areas of improvement. Accordingly, these sellers likely appreciate value-added services. Because these established, frequent users of value-added services use search advertising more than new sellers, whose primary goal is to build awareness, we expect that a seller engagement strategy appealing to established sellers (users of



Notes: The moderating roles of upmarket repositioning on both buyer- and seller-side strategies (H_7 and H_8) were tested by comparing the pairwise parameter differences estimated through vector autoregressive models run on the before- and after-repositioning periods.

Fig. 1. The effect of online shopping platform strategies on search, display, and membership revenues.

value-added services) leads to more search advertising revenue than other seller strategies.

H_4. Value-added services for sellers yield more advertising revenue than social forums.

New sellers need to generate awareness

Because display advertising is less targeted than search advertising, it draws sellers who are interested in increasing brand awareness and familiarizing buyers with their products (Forbes, 2013a). New sellers generally place a higher value on building brand awareness than established sellers, which already enjoy awareness among their target buyers. In turn, marketing initiatives designed for new sellers should generate more display advertising revenues for the platform. Social forums provide new sellers opportunities to learn best practices from veteran sellers, so sellers in these social forums likely choose display advertising more than those that prefer value-added services. That is, social forums, as a seller engagement strategy appealing to new sellers, should lead to more display advertising revenue than a value-added services strategy that appeals to established sellers.

H_5. Social forums for sellers yield more display advertising revenue than value-added services.

Established sellers likely expand their product assortments

By paying membership fees, sellers earn the right to post more products on the platform, an option that should be more appealing to sellers interested in expanding their assortments. Established sellers generally gain more value from listing a wider array of products than new sellers, which may be unsure about their commitment to the platform and start by experimenting with just a few products. Because value-added services are more valuable to established sellers that want to expand their product assortment, they should be more likely to pay a membership fee to gain such services, compared with new sellers that can remain on the site and post just a few, free product listings. That is,

H_6. Value-added services for sellers yield more membership fee revenue than social forums.

Moderating Effect of Upmarket Repositioning Strategy

Along with detailing the relative revenue effects of micro-level strategies on platform revenue streams, we study how changing the firm's value proposition toward higher-end markets, or an *upmarket repositioning strategy*, alters the effects of the buyer- and seller-side strategies on revenues. As platform firms grow, they tend to pursue upmarket repositioning strategies to enhance the quality of the online transactions. Such a macro-level change can lead to substantial changes to the platform and allow the firm to leverage the effect of its micro-level strategies on revenues. To ensure a parsimonious framework and provide concise guidance, we propose moderation hypotheses with strong theoretical support, for which we expect substantial effects.

Upmarket repositioning enhances buyers' perceived platform quality

With an upmarket repositioning strategy, buyers enjoy greater value, because low quality sellers no longer appear on the platform (Hagiu 2014). The improved quality should prompt more clicks by organic traffic buyers, who identify the platform as more reliable and valuable than other platforms, such that the effect of organic traffic on search advertising revenue increases. Similarly, the improved quality of the platform should make direct traffic buyers more receptive to display advertisements, with positive effects on display advertising revenue. However, an upmarket repositioning strategy eliminates sellers that are not qualified to remain on the platform, such that fewer sellers are able or willing to renew or sign up for membership. The positive effect of the high credibility exhibited by buyers who represent direct traffic on membership fee revenues thus might be suppressed.

H$_7$. A platform firm's upmarket repositioning strategy is associated with greater effects of (a) organic traffic on search advertising revenue and (b) direct traffic on display advertising revenue but weaker effects of (c) direct traffic on membership fee revenue.

Upmarket repositioning enhances sellers' perceived platform quality

After an upmarket repositioning, only high quality sellers remain on the platform, and they no longer have to compete with sellers supplying poor quality or counterfeit goods, which lessens these sellers' perceptions of the risks of doing business on the platform. As the platform becomes more reliable and accurate, sellers using value-added services can better target and serve buyers, which should lead buyers to click more on their listings. The seller's use of value-added services thus enhances the search advertising revenue stream after an upmarket repositioning. Sellers that use value-added services (mostly established sellers) also have more incentive to expand their product assortments on the platform, because this marketplace is more reliable and trustworthy than alternative sites. Thus, the effect of value-added services on membership fee revenue may be enhanced by an upmarket repositioning. In addition, after an upmarket repositioning, the information that sellers collect from social communities may be more insightful and less misleading. The (mostly new) sellers using social forums likely persist with their display advertising to promote brand awareness, such that the upmarket repositioning strategy is associated with a stronger effect of sellers' uses of social forums on display advertising revenue.

H$_8$. A platform firm's upmarket repositioning strategy is associated with greater effects of sellers' uses of (a) value-added services on search advertising revenue, (b) social forums on display advertising revenue, and (c) value-added services on membership fee revenue.

Methodology

Research Context and Measures

We conducted this study with the cooperation of a leading global B2B electronic platform company. It was established in 1999 in China and has become a global e-commerce leader that supports small and medium-sized businesses. The platform serves 18 million buyers and sellers, showcases products ranging from raw materials to finished goods in more than 40 industry categories, and functions as an intermediary that connects B2B buyers and sellers but does not sell its own products or services. The data span from October 1, 2010, to January 10, 2011, and then from May 1, 2011, to September 23, 2011, reflecting the periods before and after the upmarket repositioning strategy, respectively. The time series data, obtained from the global B2B online platform company, offer unique research insights. In Table 3, we summarize the constructs, definitions, and operationalizations.

Online platform revenue sources

The platform earns most of its revenue from search advertising, display advertising, and membership fees. The primary source of advertising revenue is *search advertising*. The platform offers certain keywords in auctions; in which sellers bid for their appearance and order on the results list every day—that is; pay-per-click advertising; similar to that used by many other search engine companies (e.g.; Google). Revenue from search advertising is the daily dollar advertising revenue of the platform; derived from sellers' bidding for buyers' clicks on their advertising. To earn advertising revenue from *display advertising*; the platform allows sellers to select banner; pop-up; floating; and text advertising; or some combination; to present their brand image and information for buyers. This pay-per-impression advertising entails a fixed price that can be paid daily or monthly. We measure revenue from display advertising as the daily advertising revenue derived from platform-based display advertising. In addition; revenue from *membership fees* comes from sellers that pay an annual fee; in line with a freemium model. Most sellers pay nothing; but some of them choose a premium membership and pay a fixed fee; of around $500; for the year. Sellers registered as free participants may display up to 50 products; sellers that pay the membership fees can establish their own mini-site to display unlimited products. To calculate revenue from membership fees; we measure the daily revenue from new premium members who pay the membership fee.

Buyer traffic generation strategies

Direct traffic consists of buyers that arrive at the site directly, by typing the site address or using a bookmark. We thus measure the daily number of buyers that search for products or sellers. *Referral traffic* involves buyers that search for products or sellers on external, cooperative, referral websites (e.g., expert blogs,

Table 3
Constructs, definitions, and operationalizations.

Construct	Definition	Measure
Revenue from search advertising (RS)	Revenue that a platform firm earns from hosting a keyword bidding system, in which sellers list products on the platform website and buyers search for items they seek.	Daily advertising revenue derived from platform-based bidding advertising.
Revenue from display advertising (RD)	Revenue that a platform firm earns from sellers from display advertising (e.g., pop-up advertising, floating advertising, banner advertising, and text advertising).	Daily advertising revenue derived from platform-based display advertising.
Revenue from membership fee (RM)	Revenue that a platform firm earns from sellers who paid for annual fees to list unlimited products.	Daily revenue from new premium members who pay for membership fee.
Direct traffic (DT)	Buyers who have arrived at the site directly by either typing the site address or via a bookmark.	Daily number of registered buyers who search products or sellers spontaneously.
Referral traffic (RT)	Buyers who search products or sellers through external cooperative referral websites (e.g., expert blogs, partner sites, video website, news website, soft news, and posts on social media).	Daily number of buyers who search products or sellers through the link of external websites.
Organic traffic (OT)	Buyers who search products or sellers in response to non-paid external search engine links (e.g., Google, Bing, and Baidu).	Daily number of buyers who come to the platform through external advertising links.
Sellers' use of value-added service (SV)	Sellers who use the analytical tools (e.g., accounting, stock management, consumer resource management, transaction/predictive analytic service to help sellers increase number and quality of sales) provided by the platform.	Daily number of sellers who use analytical tools provided by platform.
Sellers' use of social forum (SS)	Sellers who communicate with peer sellers through the online community.	Daily number of sellers who use the online community to interact with peer sellers.

partner sites, social media). The platform advertises on these external sites to attract potential buyers and encourage them to search its marketplace for products and sellers. Therefore, referral traffic is the daily number of buyers that search for products or sellers through a link from external websites. Finally, *organic traffic* includes buyers that search for products or sellers on non-paid, external search engines (e.g., Google, Bing, Baidu). Buyers search for a keyword, then get directed to the platform's search results page. This traffic often results from some effective advertisement or information that motivates existing or new buyers to pay attention to a specific product and engage in search behavior. We measure organic traffic as the daily number of buyers that search for products or sellers through external advertising links.

Seller engagement strategies

Value-added services and social forums for sellers function to help them resolve problems or improve their performance. *Value-added services* refer to analytical tools (e.g., accounting, stock management, consumer resource management, transaction/predictive analytic service to help sellers increase number and quality of sales) on the platform, which sellers can use to increase the level and quality of their sales. The platform's highly efficient system should improve a seller's business. We calculate the daily number of sellers that use the value-added services provided by the platform. The platform also maintains forums, blogs, and user groups that help registered members communicate and gather feedback. This *social forum* service makes communication more effective and convenient, so sellers are able to learn about the platform's policy and improve their business strategies. We measure the daily number of sellers that use the online community to interact with peer sellers.

Upmarket repositioning strategy

In response to claims of fraudulent sellers promoting counterfeit products, in February 2011, the focal platform undertook several measures that represented an upmarket repositioning. First, it eliminated more than 2,000 low quality sellers (i.e., sellers of counterfeit products) from the platform. Second, the company adopted a much more rigorous process to screen new sellers, requiring them to provide more detailed background information that allowed the platform to run thorough background checks and prevent fraudulent sellers from being listed. Third, all listed sellers were required to pay into an escrow account, called the Fair Play Fund, which would reimburse buyers in cases of product fraud. No further changes have been implemented since March 2011. Although these changes are beyond the control of individual buyers and sellers on the platforms, we acknowledge the lack of a control group for comparison. This policy shift at the platform level provides a unique quasi-experimental setting, which we exploit to examine how the causal inferences regarding the effects of micro-level strategies on revenues differ across two periods, namely, before and after the repositioning.

Model Estimation

In estimating our empirical model, we use a persistence modeling technique, the vector autoregressive (VARX) method (Dekimpe and Hanssens 1995; Pauwels and Neslin 2015; Trusov, Bucklin, and Pauwels 2009), which captures the interdependent evolution of the variables of interest through the lag of both the focal and other variables. Extant research cites the VARX model as "particularly effective in capturing the dynamic interplay among several variables" (Pauwels and Neslin 2015, p. 187). By treating each variable as potentially endogenous, this model can reveal dynamic, complex interdependence among variables of interest. It also supports a flexible treatment of the cumulative effect of strategies on revenues (Dekimpe and Hanssens 1999). Consistent with extant literature (Dekimpe and Hanssens 1999), we applied a standard VARX procedure, with separate analyses for the pre- and post-upmarket repositioning strategy periods. In H_1–H_6, we predict the effects of buyer traffic generation strategies and seller engagement strategies on revenue in the absence of an upmarket positioning strategy, so we test them using data from the period before the repositioning strategy was implemented. The pre-repositioning period also provides a baseline for testing of how the effects vary between periods (H_7–H_8), for both buyer- and seller-side strategies. We compare pairwise parameter differences, estimated through VARX, for the before- and after-repositioning periods, using the following steps

1. To test for the evolution or stationarity of the variables, we perform unit root tests. If evolution exists, we test for co-integration and structural breaks.
2. We determine the model specification (variance autoregression [VAR] in levels, VAR in differences, or error correction) according to the unit root and co-integration test results.
3. Using available information criteria, we determine the model specification (number of lags).
4. We derive impulse response functions (IRFs) for the cumulative effect.

Variable stationarity

To test how the effects vary between periods, we empirically identify the periods with a rolling-window approach (Fang et al. 2015; Joshi and Hanssens 2010). To ensure a robust model estimation, we need sufficiently long time windows, and the parameters must remain stable within each period. Our rolling-window, augmented Dickey–Fuller (ADF) unit-root tests thus include 100-day observation windows (Pauwels and Hanssens 2007; Zhang et al. 2012). For the pre-repositioning period, we moved the rolling window from October 1, 2010, to the date at which we found a structural break, that is, when the ADF test failed to reject the presence of unit roots for any of the variables (i.e., three buyer traffic generation strategies, two seller engagement strategies, three platform revenue sources) at the 5% level (see Table 4). We applied the same approach to identify the post-repositioning period, moving the rolling window backward from September 23, 2011. The results identify a 102-day span (October 1, 2010, to January 10, 2011) for the period before the upmarket repositioning, and 146 days (May 1, 2011, to September 23, 2011) for the period after it. Within each period, we perform ADF unit-root tests to address the null hypothesis (Enders 1995); the results reject the presence of unit roots for all variables at the 5% level (Table 4). No combination of evolving variables offers evidence of co-integration, so we proceed by estimating the VARX model.

With a series of Granger (1969) causality tests, we also explore whether variable X explains variable Y, beyond Y's own prior values, as a proxy for causality in time-series data. Using lags of up to 20 periods (Trusov, Bucklin, and Pauwels 2009), we investigate whether we need to model a full dynamic system. As expected, we find Granger causality in many cases, across variable pairings. For example, in both periods, growth in membership Granger-causes direct traffic, referral sites, organic traffic, sellers' use of value-added services, sellers' use of social forums, display advertising revenue, and search advertising revenue—consistent with the performance feedback effect (Dekimpe and Hanssens 1999). In addition, display advertising revenue causes direct traffic, referral sites, organic traffic, sellers' use of value-added services, sellers' use of social forums, membership fee revenue, and search advertising revenue. The Granger causality test results indicate the need to adopt a full dynamic model, such as a VARX.

Model specification

To select the VARX model, we need to determine an appropriate number of lags, so we use the Schwarz Bayesian information criterion (SBIC). A single period emerged as an appropriate lag (SBIC = 5.3326 before upmarket repositioning, SBIC = 5.8386 after upmarket repositioning). Therefore, we propose an eight-variable VARX system to capture dynamic interactions among search advertising revenue (RS), display advertising revenue (RD), membership fee revenue (RM), direct traffic (DT), referral traffic (RT), organic traffic (OT), sellers' value-added services (SV), and sellers' use of social forums (SS). Consistent with prior literature (e.g., Joshi and Hanssens 2010), we use log-transformations to normalize all variables.

The vectors of the exogenous variables include, for each endogenous variable, an intercept C; a deterministic trend variable T that captures the impact of the omitted, gradually changing trend of the variables; a seasonal dummy variable H; and indicators for the days of the week D, with Friday as the benchmark (Pauwels and Dans 2001). The VAR specification is:

Table 4
Unit root test results.

t-Value (augmented Dickey–Fuller statistic)	Before upmarket repositioning	After upmarket repositioning
Revenue from search advertising (RS)	−6.968***	−7.231***
Revenue from display advertising (RD)	−5.912***	−6.128***
Revenue from membership fee (RM)	−8.192***	−8.462***
Direct traffic (DT)	−4.129***	−4.491***
Referral traffic (RT)	−9.847***	−10.115***
Organic traffic (OT)	−7.483***	−8.922***
Sellers's use of value-added service (SV)	−10.493***	−11.611***
Sellers' use of social forums (SS)	−5.226***	−6.593***

Notes: All variables are log-transformed.
*$p < .10$.
**$p < .05$.
***$p < .01$.

$$\begin{bmatrix} \ln RS_t \\ \ln RD_t \\ \ln RM_t \\ \ln DT_t \\ \ln RT_t \\ \ln OT_t \\ \ln SV_t \\ \ln SS_t \end{bmatrix} = \begin{bmatrix} C_{RS} \\ C_{RD} \\ C_{RM} \\ C_{DT} \\ C_{RT} \\ C_{OT} \\ C_{SV} \\ C_{SS} \end{bmatrix} + \begin{bmatrix} \delta_{RS} \\ \delta_{RD} \\ \delta_{RM} \\ \delta_{DT} \\ \delta_{RT} \\ \delta_{OT} \\ \delta_{SV} \\ \delta_{SS} \end{bmatrix} \times T + \begin{bmatrix} \theta_{RS} \\ \theta_{RD} \\ \theta_{RM} \\ \theta_{DT} \\ \theta_{RT} \\ \theta_{OT} \\ \theta_{SV} \\ \theta_{SS} \end{bmatrix} \times \mathrm{H} + \begin{bmatrix} \gamma_{RS} \\ \gamma_{RD} \\ \gamma_{RM} \\ \gamma_{DT} \\ \gamma_{RT} \\ \gamma_{OT} \\ \gamma_{SV} \\ \gamma_{SS} \end{bmatrix}$$

$$\times \mathrm{D} + \sum_{j=1}^{J} \begin{bmatrix} \phi_{11}^j & \phi_{12}^j & \phi_{13}^j & \phi_{14}^j & \phi_{15}^j & \phi_{16}^j & \phi_{17}^j \\ \phi_{21}^j & \phi_{22}^j & \phi_{23}^j & \phi_{24}^j & \phi_{25}^j & \phi_{26}^j & \phi_{27}^j \\ \phi_{31}^j & \phi_{32}^j & \phi_{33}^j & \phi_{34}^j & \phi_{35}^j & \phi_{36}^j & \phi_{37}^j \\ \phi_{41}^j & \phi_{42}^j & \phi_{43}^j & \phi_{44}^j & \phi_{45}^j & \phi_{46}^j & \phi_{47}^j \\ \phi_{51}^j & \phi_{52}^j & \phi_{53}^j & \phi_{54}^j & \phi_{55}^j & \phi_{56}^j & \phi_{57}^j \\ \phi_{61}^j & \phi_{62}^j & \phi_{63}^j & \phi_{64}^j & \phi_{65}^j & \phi_{66}^j & \phi_{67}^j \\ \phi_{71}^j & \phi_{72}^j & \phi_{73}^j & \phi_{74}^j & \phi_{75}^j & \phi_{76}^j & \phi_{77}^j \\ \phi_{81}^j & \phi_{82}^j & \phi_{83}^j & \phi_{84}^j & \phi_{85}^j & \phi_{86}^j & \phi_{87}^j \end{bmatrix} \begin{bmatrix} \ln RS_{t-j} \\ \ln RD_{t-j} \\ \ln RM_{t-j} \\ \ln DT_{t-j} \\ \ln RT_{t-j} \\ \ln OT_{t-j} \\ \ln SV_{t-j} \\ \ln SS_{t-j} \end{bmatrix}$$

$$+ \begin{bmatrix} \varepsilon_{RS,t} \\ \varepsilon_{RD,t} \\ \varepsilon_{RM,t} \\ \varepsilon_{DT,t} \\ \varepsilon_{RT,t} \\ \varepsilon_{OT,t} \\ \varepsilon_{SV,t} \\ \varepsilon_{SS,t} \end{bmatrix}, \tag{1}$$

where t refers to days, j equals the number of lags included (determined on the basis of the SBIC), H is the seasonal dummy variable, D is the vector for the day-of-week dummies, and ε are white-noise disturbances distributed as N(0, Σ). The parameters δ, θ, γ, and ϕ are estimated. Because the VARX model parameters are not interpretable on their own (Sims 1980), we determine the effect sizes and significance through an analysis of IRFs and elasticity, computed from our model.

Impulse response functions

We derive IRFs, which trace the over-time impact of a unit shock to any endogenous variable on other endogenous variables. Following Dekimpe and Hanssens (1999), we use generalized IRFs (or simultaneous shocking) to ensure that the order of variables in the system does not affect the results, as well as to account for contemporaneous same-period effects. Following extant research (Dekimpe and Hanssens 1999; Joshi and Hanssens 2010; Nijs et al. 2001), we determine the duration of the shock (maximum lag k) as equal to the last period in which the IRF value had a |t| statistic greater than 1. We accumulate IRFs until lag k, as the cumulative effect of the unexpected shock in the impulse variable on the response variable.

Results

We are interested in the cumulative effect of buyer traffic generation strategies and seller engagement strategies on three revenue sources. The revenue sources and strategy variables are all log-transformed, so the coefficients can be interpreted as elasticity. In Table 5, we summarize the results by presenting the estimates and number of days that each effect lasted.

Effect of Buyer Traffic Generation Strategies on Platform Revenue Sources

Before the upmarket repositioning strategy, organic (elasticity = .074, $p < .01$) and referral (elasticity = .084, $p < .01$) traffic had significant positive effects on search advertising revenue, but direct traffic did not significantly improve search advertising revenue (elasticity = .022, *n.s.*). For the pairwise comparisons of the cumulative effects, we use Monte Carlo simulations with 250 replications (Villanueva, Yoo, and Hanssens 2008), then apply the same approach for all subsequent pairwise comparisons. The difference between the effects of organic and referral traffic on search advertising revenue is not significant (difference = −.010, *n.s.*), so we reject H_{1a}: Referral traffic is just as effective as organic traffic in generating search advertising rev-

Table 5
Estimation results: the effect of online shopping platform strategies on search, display, and membership revenues.

Path tested		Before upmarket repositioning		After upmarket repositioning		Pairwise difference (after–before repositioning)	
		Estimate	Number of days	Estimate	Number of days		Estimate
Effects of buyer traffic generation strategies on search advertising revenue							
Direct traffic → search advertising revenue		.022	N.S.	.031*	1		.009
Referral traffic → search advertising revenue		.084***	2	.122***	3		.038*
Organic traffic → search advertising revenue		.074***	4	.131***	5	**H$_{7a}$**	**.057****
Pairwise difference (organic—referral traffic → search advertising revenue)	**H$_{1a}$**	−**.010**					
Pairwise difference (organic—direct traffic → search advertising revenue)	**H$_{1b}$**	**.052****					
Effects of buyer traffic generation strategies on display advertising revenue							
Direct traffic → display advertising revenue		.274***	11	.338***	1	**H$_{7b}$**	**.064****
Referral traffic → display advertising revenue		.056**	1	.068***	1		.012
Organic traffic → display advertising revenue		.008	N.S.	.011	N.S.		.002
Pairwise difference (direct—referral traffic → display advertising revenue)	**H$_{2a}$**	**.218*****					
Pairwise difference (direct—organic traffic → display advertising revenue)	**H$_{2b}$**	**.266*****					
Effects of buyer traffic generation strategies on membership fee revenue							
Direct traffic → membership fee revenue		.052**	5	.034*	4	**H$_{7c}$**	−**.018**
Referral traffic → membership fee revenue		.004	N.S.	.001	N.S.		−.003
Organic traffic → membership fee revenue		.041**	3	.021	N.S.		−.020
Pairwise difference (direct—referral traffic → membership fee revenue)	**H$_{3a}$**	**.048****					
Pairwise difference (direct—organic traffic → membership fee revenue)	**H$_{3b}$**	**.011**					
Effects of seller engagement strategies on search advertising revenue							
Sellers' use of value-added services → search advertising revenue		.038**	2	.073***	3	**H$_{8a}$**	**.035***
Sellers' use of social forums → search advertising revenue		.004	N.S.	.006	N.S.		.002
Pairwise difference (value-added services—social forum → search advertising revenue)	**H$_4$**	**.034****					
Effects of seller engagement strategies on display advertising revenue							
Sellers' use of value-added services → display advertising revenue		.076***	1	.073***	3		−.003
Sellers' use of social forums → display advertising revenue		.154***	7	.198***	7	**H$_{8b}$**	**.044****
Pairwise difference (social forum—value-added services → display advertising revenue)	**H$_5$**	**.078*****					
Effects of seller engagement strategies on membership fee revenue							
Sellers' use of value-added services → membership fee revenue		.123***	2	.189***	2	**H$_{8c}$**	**.066****
Sellers' use of social forums → membership fee revenue		.102***	2	.112***	2		.014
Pairwise difference (value-added services—social forum → membership fee revenue)	**H$_6$**	**.021***					

* $p < .10$.
** $p < .05$.
*** $p < .01$.

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enues. But the pairwise comparison of the effects of organic and direct traffic on search advertising revenue is significant (difference = .052, $p < .05$), so in support of H_{1b}, the positive effect of traffic generation strategies on search advertising revenue is greater for organic than for direct traffic.

Also before the upmarket repositioning, direct (elasticity = .274, $p < .01$) and referral (elasticity = .056, $p < .05$) traffic indicate significant positive effects on display advertising revenue, but organic traffic offers no significant impact (elasticity = .008, *n.s.*). The pairwise difference between the influence of direct and referral traffic on display advertising revenue is significant (difference = .218, $p < .01$), in support of H_{2a}. The positive effect of buyer traffic generation strategies on display advertising revenue is greater for direct traffic than for referral traffic. The pairwise comparison between direct and organic traffic with regard to display advertising revenue is significant too (difference = .266, $p < .01$), in support of H_{2b}, and the positive effect of traffic generation strategies on display advertising revenue is greater for direct than for organic traffic.

Finally, direct (elasticity = .052, $p < .05$) and organic (elasticity = .041, $p < .05$) traffic exert significant positive effects on membership fee revenues, but referral traffic does not (elasticity = .004, *n.s.*). The pairwise difference in the effect between direct and referral traffic on membership fee revenue is significant (difference = .048, $p < .05$), such that the positive effect of buyer traffic generation strategies on membership fee revenues is greater for direct than for referral traffic, in support of H_{3a}. The pairwise comparison involving direct and organic traffic is not significant though (difference = .011, *n.s.*); we cannot confirm H_{3b}, because organic traffic appears just as effective as direct traffic for generating membership fee revenue.

Effect of Seller Engagement Strategies on Platform Revenue Sources

Prior to the upmarket repositioning, the seller's use of value-added services had a significant, positive effect on search advertising revenue (elasticity = .038, $p < .05$), but the seller's use of social forums had no significant impact (elasticity = .004, *n.s.*). This pairwise difference, between the effects of value-added services and social forums on search advertising revenue, is significant (difference = .034, $p < .05$), in support of H_4; the positive effect of seller engagement strategies on search advertising revenue is greater due to value-added services rather than social forums. With regard to display advertising, the uses of both value-added services and social forums have significant, positive effects (elasticity = .076, $p < .01$; .154, $p < .01$, respectively). The pairwise difference also is significant (difference = .078, $p < .01$), so we confirm H_5, in which we predicted that the positive effect of seller engagement strategies on search advertising revenue would be greater for a seller's use of social forums than its use of value-added services. Finally, both value-added services and social forums exert significant, positive effects on membership fee revenue (elasticity = .123, $p < .01$; .102, $p < .01$, respectively). The pairwise difference is marginally significant (difference = .021, $p < .10$), in marginal support of H_6: A seller's use of social forums generates marginally higher membership fee revenue than its use of value-added services.

Moderating Effect of Upmarket Repositioning Strategy

Organic traffic indicates a significant positive effect on search advertising revenue before (elasticity = .074, $p < .01$) and after (elasticity = .131, $p < .01$) the upmarket repositioning. In support of H_{7a}, the positive effect of organic traffic is even greater after the upmarket repositioning than before (difference = .057, $p < .05$). Direct traffic has significant, positive effects on display advertising revenue before (elasticity = .274, $p < .01$) and after (elasticity = .338, $p < .01$) the upmarket repositioning, and in support of H_{7b}, the positive effect of direct traffic is greater after than before (difference = .064, $p < .05$). Despite the significant, positive effects of direct traffic on membership fee revenue before (elasticity = .052, $p < .01$) and after (elasticity = .034, $p < .01$) the upmarket repositioning, the positive effect of direct traffic does not diminish significantly after compared with before the strategy change (difference = −.018, *n.s.*), so we cannot confirm H_{7c}.

Regarding the seller's use of value-added services, we find significant, positive effects on search advertising revenue before (elasticity = .038, $p < .05$) and after (elasticity = .073, $p < .01$) the upmarket repositioning. In support of H_{8a}, the positive effect of value-added services is marginally greater after than before the upmarket repositioning (difference = .035, $p < .10$). The seller's use of social forums similarly has significant, positive effects on display advertising revenue before (elasticity = .154, $p < .01$) and after (elasticity = .198, $p < .01$) the upmarket repositioning. As we predicted in H_{8b}, the positive effect of social forums is greater after the repositioning strategy than before (difference = .044, $p < .05$). Finally, the seller's use of value-added services has significant, positive effects on membership fee revenue, both before (elasticity = .123, $p < .01$) and after (elasticity = .189, $p < .01$) the repositioning; in support of H_{8c}, this positive effect is greater after the repositioning (difference = .066, $p < .05$).

Economic Returns from Buyer- and Seller-Side Strategies

The empirical support we obtained from these findings offers confidence in our theoretical framework, but it cannot inform managers about the ultimate consequences of these strategies. To provide additional insight for practitioners, we conducted post hoc analyses of the returns on investments in buyer traffic generation strategies and seller engagement strategies. Using the estimates from Table 5, we first performed elasticity analyses, then calculated revenue gains due to a 1% increase in buyer- or seller-side strategies, according to the three revenue sources. We multiplied each elasticity by the average daily revenues earned through these three revenue sources, before and after an upmarket repositioning strategy. That is, we *decomposed the economic returns for each micro strategy* (direct, referral, organic, value-added services, social forums) *across three revenue sources* (search advertising, display advertising, membership fee) *and* *compared the monetary returns before and after the upmarket repositioning*.

The economic returns appear in Table 6, reflecting the revenue gains from a 1% increase in each strategy variable, displayed as a percentage to indicate the proportion of the dollar amount, in terms of the revenue increase due to the strategy. For example, before an upmarket repositioning strategy, a 1% increase in direct traffic generated total revenues of $319,559, of which 57% came from display advertising revenue ($180,996), 42% from membership fee revenue ($133,551), and 2% from search advertising revenue ($5,012). After the repositioning, a 1% increase in direct traffic instead generated $445,198 of total revenue, of which 75% was generated by direct traffic through display advertising revenue ($332,502), 17% through membership fee revenue ($75,391), and 8% through search advertising revenue ($37,305).

With these economic returns specified, we can compare the magnitude of changes by identifying which combinations of strategies and revenue sources excel most. Before the upmarket repositioning, direct traffic is the most effective means to increase platform revenues earned through display advertising and membership fees. Among the buyer- and seller-side strategies, sellers' use of value-added services is the most effective means to increase platform revenue through membership fees (1% increase generates $315,898). Sellers' use of social forums is twice as effective as their use of value-added services for generating display advertising revenue ($101,728 from social forums, $50,203 from value-added services). After the upmarket repositioning, the search advertising revenue returns obtained from organic traffic increase by 136% (1% increase in organic traffic generates $66,892 before and $157,645 after), and those resulting from the seller's use of value-added services increase by 156% (1% increase in value-added services generates $34,350 before and $87,848 after). Thus, platform firms must prioritize their buyer- and seller-side strategies precisely, depending on the source of revenue they seek to increase (search advertising, display advertising, or membership fees).

Discussion

Our holistic, conceptual framework sheds new light on online platform business models by combining three distinctive revenue sources (i.e., search advertising, display advertising, and membership fees) and buyer- and seller-side strategies. With a unique quasi-experiment, we examine which buyer traffic generation and seller engagement strategies generate the most, in terms of each revenue source, as well as how their effectiveness shifts due to an upmarket repositioning strategy. Our findings produce both theoretical and managerial insights.

Theoretical Implications

This study offers a comprehensive framework with respect to three different platform revenue streams, each operating in a different way (Fig. 1). With the recognition that "many online businesses combine multiple revenue streams" (Lambrecht et al. 2014, p. 332), yet that most extant findings focus on individual revenue sources (Fang et al. 2015; Tucker and Zhang 2010) or on an aggregate level of revenues (Grewal, Chakravarty, and Saini 2010; Zhang et al. 2012), this article offers a more complete picture of online platform business models.

In terms of buyer-side strategies, our study demonstrates that organic traffic effectively generates search advertising revenue, more so than direct traffic, likely because these buyers search for and click on seller and product information, for which the sellers pay. In contrast, direct traffic leads to more display advertising revenue than organic traffic. Therefore, direct traffic buyers may be more receptive to information and advertising cues initiated by the platform, which leads sellers to increase their participation in display advertising. In terms of generating membership fee revenue, direct traffic yields more than organic traffic; sellers likely commit to pay a membership fee if buyers are ready to close more sales.

In relation to seller-side strategies, our results also show that (1) established sellers are better able to target using search, (2) new sellers need to generate awareness, and (3) established sellers are more likely to expand their product assortments. If the platform wants to generate more search advertising revenue, it should turn to established rather than new sellers, because they are better able to target buyers. For display advertising revenue, new sellers instead yield more, because they want to promote brand awareness, which increases their participation in display advertising. Finally, established sellers generate more membership fee revenues than new sellers, because they want to expand their product assortments beyond free membership levels.

Raising the level of platform quality through upmarket repositioning can lead to greater positive effects of organic traffic on search advertising and of direct traffic on display advertising revenues. It also augments the positive effects of the seller's use of value-added services on search advertising and membership revenues and of the seller's use of social forums on display advertising revenue. To recapitulate, we offer a summary of hypotheses and findings in Table 7.

Managerial Implications

For online platform firms, our study provides several practical and managerial insights. First, our findings offer a clearer understanding of multiple revenue sources. To generate revenue from sellers, platforms often combine multiple business models; for example, on Alibaba, "merchants pay an annual fee of $5,000 to $10,000, along with a $25,000 refundable deposit . . . [and] 3% to 6% commissions on each sale" (The Wall Street Journal 2014). Then it charges 1 million Yuan (or $162,460) daily for display advertisements on its website (The Wall Street Journal 2015). These tremendous dollar values indicate that platform firms must remain cognizant of how their revenue depends on their ability to pair buyers and sellers effectively.

Second, buyers' perceptions of the quality of the sellers and the platform determine the revenue effects of a platform firm's marketing strategies. Direct traffic accounts for the most profitable buyers, especially before the platform adopts an upmarket repositioning strategy. These buyers are associated with the highest levels of platform familiarity, and it is critical to continue

Table 6
Economic returns from buyer- and seller-side strategies: before and after upmarket repositioning strategy.

	Before upmarket repositioning				After upmarket repositioning			
	Search advertising revenue gains	Display advertising revenue gains	Membership fee revenue gains	Total revenue	Search advertising revenue gains	Display advertising revenue gains	Membership fee revenue gains	Total revenue
Direct traffic								
1% increase on revenue gain	$ 5,012	$ 180,996	$ 133,551	$ *319,559*	$ 37,305	$ 332,502	$ 75,391	$ *445,198*
As a % of total revenues	2%	57%	42%	100%	8%	75%	17%	100%
Referral traffic								
1% increase on revenue gain	$ 75,932	$ 36,992	$ 10,233	$ *123,157*	$ 146,814	$ 66,894	$ 11,682	$ *225,390*
As a % of total revenues	62%	30%	8%	100%	65%	30%	5%	100%
Organic traffic								
1% increase on revenue gain	$ 66,892	$ 9,282	$ 105,299	$ *181,474*	$ 157,645	$ 9,837	$ 2,673	$ *170,155*
As a % of total revenues	37%	5%	58%	100%	93%	6%	2%	100%
Sellers' use of value-added services								
1% increase on revenue gain	$ 34,350	$ 50,203	$ 315,898	$ *400,452*	$ 87,848	$ 71,813	$ 419,085	$ *578,746*
As a % of total revenues	9%	13%	79%	100%	15%	12%	72%	100%
Sellers' use of social forums								
1% increase on revenue gain	$ 5,768	$ 101,728	$ 261,965	$ *369,460*	$ 6,447	$ 194,779	$ 248,347	$ *449,573*
As a % of total revenues	2%	28%	71%	100%	1%	43%	55%	100%

Notes: In this table, we report the dollar amount to represent the revenue gains from 1% increase in a strategy variable, then display this dollar amount as a percentage to show the proportional revenue increase from the strategy. For example, in the total revenue column for direct traffic, before the upmarket repositioning strategy, a 1% increase in direct traffic generated total revenues of $319,559, and 57% of this total revenue comes through display advertising revenue ($180,996) versus 42% from membership fee revenue ($133,551). After repositioning, a 1% increase in direct traffic generated display advertising revenues of $332,502, which accounts for 75% of the total revenue generated by direct traffic.
Percentages may not total 100 due to rounding.

Table 7
Summary of hypotheses and findings.

Hypotheses		Findings
Effect of buyer traffic generation strategies on revenue		
H_{1a}	Organic traffic yields more search advertising revenue than referral traffic.	✗
H_{1b}	Organic traffic yields more search advertising revenue than direct traffic.	✓
H_{2a}	Direct traffic yields more display advertising revenue than referral traffic.	✓
H_{2b}	Direct traffic yields more display advertising revenue than organic traffic.	✓
H_{3a}	Direct traffic yields more membership fee revenues than referral traffic.	✓
H_{3b}	Direct traffic yields more membership fee revenues than organic traffic.	✗
Effect of seller engagement strategies on revenue		
H_4	Value-added services for sellers yield more advertising revenue than social forums.	✓
H_5	Social forums for sellers yield more display advertising revenue than value-added services.	✓
H_6	Value-added services for sellers yield more membership fee revenue than social forums.	✓
Effects of upmarket repositioning strategy on revenue		
H_{7a}	A platform firm's upmarket repositioning strategy is associated with greater effects of organic traffic on search advertising revenue.	✓
H_{7b}	A platform firm's upmarket repositioning strategy is associated with greater effects of direct traffic on display advertising revenue.	✓
H_{7c}	A platform firm's upmarket repositioning strategy is associated with weaker effects of direct traffic on membership fee revenue.	✗
H_{8a}	A platform firm's upmarket repositioning strategy is associated with greater effects of sellers' uses of value-added services on search advertising revenue.	✓
H_{8b}	A platform firm's upmarket repositioning strategy is associated with greater effects of sellers' uses of social forums on display advertising revenue.	✓
H_{8c}	A platform firm's upmarket repositioning strategy is associated with greater effects of sellers' uses of value-added services on membership fee revenue.	✓

Notes. ✓: hypothesis supported; ✗ : hypothesis not supported.

fostering their sense of the reliability of the platform and encourage them to visit it often. Regardless of whether it implements an upmarket repositioning strategy, sellers' uses of value-added services represent the most effective means for increasing the platform's revenues from membership fees. Specifically, our post hoc analysis in this case indicates that sellers' use of value-added services is the most effective means to increase platform revenues through membership fees (1% increase in direct traffic generates an incremental $315,898), among all available strategies. There is no panacea; managers must determine which seller engagement strategy works best for their unique platform features. As the CEO of Source4Style recognizes, suppliers "want a more practical tool to help them streamline their leads, follow up with potential buyers and track conversions from sample requests to purchase orders" (Forbes, 2013b).

Third, many firms face the threat of failure due to their "lemon markets," such that low quality sellers drive out the high-quality ones (Hagiu 2014). Our finding emphasizes the value of transparent, sufficient information for buyers. Poor product quality diminishes trust (Shankar, Urban, and Sultan 2002), and low quality sellers even might lead to costly lawsuits for the platform (The New York Times 2015). As we show, an upmarket repositioning strategy can enhance the effects of buyer- and seller-side strategies on platform revenues—with the exception of the impact of direct traffic on membership fee revenues. That is, a 1% increase in direct traffic contributed to $133,551 in membership fee revenues before the upmarket repositioning strategy but only $75,391 after. Beyond this exception, our findings affirm that for achieving platform success, "The primary factors are increasing the quality of matches between complementary users and charging the most competitive fees" (strategy+business 2013). Some of noteworthy findings from the post-hoc analyses are that after (vs. before) upmarket repositioning, a 1% increase in direct traffic leads to additional display advertising revenues of $151,506, and a 1% increase in organic traffic generates additional search advertising revenues of $90,753—equivalent to 136% growth. The 1% increase in value-added services and additional search advertising revenue of $53,498 implies 156% growth. Therefore, online platform firms can benefit greatly from precisely prioritizing their micro- (buyer- and seller-side) and macro-level (upmarket repositioning) strategies, depending on the focal revenue sources.

Limitations and Research Directions

This study examines an important topic, but it is subject to several limitations. First, we focused on a single, transactional, online shopping platform. Additional studies should extend our research to other platforms and contexts, such as informational platforms, where competition among content providers may differ from that among the sellers on a transactional platform. Such differences also might determine which revenue models work best for which platform companies. Second, data limitations meant that we considered data only at the platform level. Further studies might gather more detailed, heterogeneous, individual-level buyer and seller information, such as capabilities or sizes, which may affect behaviors and performance. Third, we focused on an online platform channel. As traditional e-commerce firms, such as Amazon, continue to build their online platforms (Amazon Marketplace), they have created new, hybrid forms that feature both in-house and platform operations. Continued research could investigate how buyer-and seller-side strategies need to adjust for such hybrid models. Fourth, additional dimensions might characterize inbound traffic types, such as the duration of the buyer's prior experience with the seller or psychological involvement with the platform. Continued research should test these mechanisms.

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