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Feng Zhu
Qihong Liu

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Feng Zhu
Harvard Business School

Qihong Liu
University of Oklahoma

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Feng Zhu
Harvard University
Boston, MA 02163
Email: fzhu@hbs.edu

Qihong Liu
University of Oklahoma
Norman, OK 73019
Email: qliu@ou.edu

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Abstract

Platform owners sometimes enter complementors' product spaces to compete against them directly. Prior studies have offered two possible explanations for such entries: platform owners may target the most successful complementors so as to appropriate value from their innovations, or they may target poor performing complementors to improve the platforms' overall quality. Using data from Amazon.com, we analyze the patterns of Amazon's entry into its third-party sellers' product spaces. We find evidence consistent with the former explanation: that the likelihood of Amazon's entry is positively correlated with the popularity and customer ratings of third-party sellers' products. We also find that Amazon's entry reduces the shipping costs of affected products and hence increases their demand. Results also show that small third-party sellers affected by Amazon's entry appear to be discouraged from growing their businesses on the platform subsequently. The results have implications for complementors participating in various platform-based markets.

1 Introduction

Platform-based markets have become increasingly prevalent, and comprise a large and rapidly growing share of today's economy (e.g., Eisenmann 2007). Such markets are often described as multi-sided because multiple groups of participants—such as consumers and complementors—need to gain access to the same platform to interact with each other, and a platform's success depends on its ability to bring them on board (e.g., Rochet and Tirole 2003; Parker and Van Alstyne 2005). Examples of such markets are as diverse as video game consoles, smartphones, online auction markets, search engines, and social networking sites. Thousands of entrepreneurs have built businesses and sell products and services on such platforms. Collectively, these entrepreneurs—who operate as complementors to the platforms—create significant value. By the end of 2014, for example, more than 1.7 million and 1.4 million applications had been developed for two popular smartphone platforms, Google's Android and Apple's iOS, respectively, generating billions of dollars of revenue for each platform owner.[1]

At the same time, platform owners can exert considerable influence over individual complementors' livelihoods. In particular, they may choose to imitate successful complementors and offer similar products. Many complementors have been pushed out of their markets not by competition from other complementors, but because platform owners compete directly against them and appropriate the value from their innovations. For example, Netscape and Real Networks, complementors on Microsoft's Windows platform, were extinguished by rival Microsoft applications Internet Explorer and Windows Media Player; microblogging platform Twitter's release of its own client applications for mobile devices effectively locked out third-party client applications; and Apple makes some previously essential third-party apps

[1] Source: Graser M. 2015. Apple doubles app store sales in 2014, setting a record. *Variety*. 19 January: `http://variety.com/2015/digital/news/apple-doubles-app-store-sales-in-2014-setting-a-record-1201396900/`, accessed August 2015.

obsolete with every new operating system it releases[2]—and sometimes simply rejects apps for its devices if they compete with its own current or planned offerings.[3]

Such strategic behavior on the part of platforms should come as no surprise. Recent studies on inter-organizational relationships suggests that interdependence may expose young firms with high resource needs and high value innovations to the risk of value misappropriation (e.g., Gans and Stern 2003; Katila et al. 2008; Diestre and Rajagopalan 2012; Huang et al. 2013; Hallen et al. 2013; Pahnke et al. forthcoming). Complementors in platform-based markets are vulnerable to such risks, as they depend entirely on the platforms to reach their customers. Typically small relative to platforms, they often lack adequate resources to protect their innovations. In a similar vein, the literature on co-opetition has long held that companies may be collaborators with respect to value creation but become competitors when it comes to value capture (e.g., Brandenburger and Nalebuff 1997). In platform-based markets, one strategy platforms employ to capture value from or limit the bargaining power of complementors is to imitate their successful products (e.g., Farrell and Katz 2000).

On the other hand, squeezing complementors can have negative consequences for a platform owner, who will not generally have the capabilities to enter all possible complementary markets, and so must encourage the widespread entry of complementors to grow its market. A platform that enters a complementor's product space signals to all complementors that they may not, in the end, be able to capture value from their innovations, leading current complementors to switch to, and potential complementors to affiliate with, other platforms. Gans and Stern (2003) point that rather than exploiting all opportunities to gain, a firm can

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[2]See, for example, Smith K. 2012. 10 popular Mac apps that Apple's new operating system just made obsolete. *Business Insider*. 25 July: `http://www.businessinsider.com/mountain-lion-apps-2012-7?op=1`, accessed August 2015.

[3]See, for example, Rosenberg D. 2008. Apple blocks competitive products from iPhone App Store–surprised?. *CNET*. 13 September: `http://www.cnet.com/news/apple-blocks-competitive-products-from-iphone-app-store-surprised/` and Singel R. 2009. Apple rejects Google voice app, invites regulation. *Wired*. 28 July: `http://www.wired.com/2009/07/apple-rejects-google-voice/`,, accessed August 2015.

develop a reputation for "fairness" to encourage future start-ups to approach them with new innovations. Iansiti and Levien (2004) suggest, consistent with these arguments, that platforms need to maintain the health of their entire ecosystem for the simple reason that their survival depends on doing so. Gawer and Henderson (2007) conduct a detailed case study of Intel. They show that Intel does not enter to compete with complementors' products, except when complementors' products contain new platform interfaces. Even when Intel chooses to enter its complementors' markets, the company uses certain organizational structures and processes to signal it still wants the complementors to make money. Gawer and Cusumano (2002) document that Intel enters certain complementary markets when it is not satisfied with these complementors' performance and wants to use competition to stimulate their innovation efforts.

Overall, despite its importance, we have scant empirical evidence to help us understand platform owners' strategies with respect to complementary markets. While there have been a few high-profile examples, it remains unclear how often platform owners enter their complementors' markets. What are the dominant motivations behind such entries: are platform owners more likely to target successful complementary products, or are they more likely to target underperforming complementary products, which are often less likely to be noticed, seeking to improve customer satisfaction? How are the consumers and complementors affected by such platform owner entries? Answers to these questions have important implications for complementors' strategies and consumer welfare.

Our research seeks to answer these questions using data from Amazon.com, which is both the largest online retailer in the United States and a platform on which third-parties can sell products directly to customers. This empirical setting allows us to systematically analyze a platform owner's incentives to enter (or not to enter) a wide range of complementary product spaces. None of these complementary products embody new platform interfaces. We collect data from Amazon in two rounds. In the first round, we identify a large set of products offered by third-party sellers, and in the second, we check whether Amazon has chosen to enter their product spaces. We find that Amazon entered 3% of complementors' product spaces over a 10-month period. We also find that Amazon is more likely to enter when third-party products have higher sales and better reviews, and do not use Amazon's fulfilment service. Using propensity-score matching to compare products affected and unaffected by Amazon's entry, we find entry to increase product demand by virtue of reducing shipping costs to consumers. At the same time, small third-party sellers affected by Amazon's entry appear to be discouraged from growing their businesses on Amazon.com.

1.1 Related Literature

Our paper contributes to three streams of literature. We add to the nascent stream of research on platform-based markets, which currently centers on platform owners as the focal point of interest. Scholars have examined platform owners' pricing decisions on different sides of the market (e.g., Rochet and Tirole 2003; Parker and Van Alstyne 2005; Hagiu 2006; Chen et al. 2012; Seamans and Zhu 2014; Hao and Fan forthcoming), interactions between competing platforms (e.g., Armstrong 2006; Economides and Katsamakas 2006; Casadesus-Masanell and Llanes 2011), the value of installed bases to platform owners seeking to diversify into other markets (e.g., Eisenmann et al. 2011; Edelman forthcoming) or to introduce next-generation platforms (e.g., Claussen et al. 2015; Kretschmer and Claussen 2015), platform owners' management of complementors (e.g., Yoffie and Kwak 2006; Parker and Van Alstyne 2014; Cennamo and Panico 2015; Cennamo and Santalo 2015), timing of new platform owners' entry into platform-based markets (e.g., Zhu and Iansiti 2012), optimal information disclosure (e.g., Dai et al. 2014; Nosko and Tadelis 2015), and platform governance choices such as those regarding exclusivity and limiting the variety of applications (Cennamo and Santalo 2013; Casadesus-Masanell and Halaburda 2014). Studies of complementors tend to focus on positive outcomes of affiliating with platform owners, given that platforms provide complementors access to their installed bases (e.g., Venkatraman and Lee 2004; Ceccagnoli et al. 2012; Claussen et al. 2013). The few studies that acknowledge potential expropriation threats from platform owners lack evidence of platform owners' entry patterns (Farrell and Katz 2000; Jiang et al. 2011; Huang et al. 2013).

Our paper informs as well the literature on inter-organizational relationships, much of which also emphasizes positive outcomes for participating firms (e.g., Eisenhardt and Schoonhoven 1996; Rothaermel 2001, 2002; Gulati and Higgins 2003; Gulati et al. 2009) and the value creation role played by hub firms in inter-organizational networks (e.g., Kapoor and Lee 2013). Consistent with resource dependence theory, which identifies interdependence as the key motivator of tie formation (e.g., Ozcan and Eisenhardt 2009), studies in the inter-organization literature often find complementors to be more likely to form ties with dominant platform owners. The few studies that explore potential problems of value misappropriation, known as the "swimming with sharks" dilemma, largely focus on whether small firms should establish ties with large firms (e.g., Katila et al. 2008; Diestre and Rajagopalan 2012; Huang et al. 2013; Hallen et al. 2013; Pahnke et al. forthcoming). Although all identify tensions between small firms' resource needs and the risk of value misappropriation, these studies do not address this risk in situations where firms are obliged to form ties with large partners if they want to create value in the first place, as they are in platform-based markets.

The platform-based market setting also differs from conventional supply chains. For example, merchants like CVS, one of the largest U.S. pharmacy chains, buy products from their suppliers and then resell them to consumers. They may choose to offer their private labels to compete with their suppliers. In such cases, merchants bear all the cost of experimentation (e.g., promotion and logistics costs). In the platform setting, complementors bear the cost of experimentation for their products. They devote efforts into discovering innovative and interesting products that, in their absence, might never have occurred to platform owners to offer. They often pay platform owners to promote these products as well. For example, many third-party sellers on Amazon.com pay Amazon to advertise their products on its site. Therefore, complementors in platform-based markets create substantially more value than upstream suppliers in supply chains. Neither do merchants' private label entries typically push suppliers out of the market. Extant research on merchants' entry into suppliers' product spaces tends to find the formers' products to be of lower quality and, in equilibrium, to co-exist with suppliers' products by targeting consumer segments with different price sensitivities (e.g., Chintagunta et al. 2002; Steenkamp and Kumar 2007; Yehezkel 2008).

Lastly, our paper relates to the literature on co-opetition (Brandenburger and Nalebuff 1997), which describes situations in which the value of a product is created by firms that subsequently compete to extract profit from it. The relationship between Intel and Microsoft is a prominent example of co-opetition (Casadesus-Masanell and Yoffie 2007; Casadesus-Masanell et al. 2007): here Microsoft's dependence on its installed base of PCs and Intel's dependence on new PC sales create conflict over their incentives to invest in new generations of PCs. In our setting, Amazon and third-party sellers cooperate to create value for customers, but can come into conflict about how to divide up the pie. Direct entry into their product spaces is one way Amazon can capture more of the value jointly created with third-party sellers. The relationships in our setting differ from that between Intel and Microsoft in that platform owners (e.g., Amazon) are much more powerful than complementors (e.g., individual third-party sellers). Our results highlight the importance of small firms considering value capture more seriously when entering into value-creating partnerships with large firms.

The rest of the paper proceeds as follows. Section 2 discusses our empirical setting. Section 3 discusses our data and variables. Section 4 presents our empirical results. We discuss managerial implications and conclude in Section 5.

2 Empirical Setting

Founded on July 5, 1994 as an online reseller of books, Amazon.com, Inc. quickly diversified into many other product categories including DVDs, CDs, video games, apparel, furniture, toys, and jewelry. Today it is the largest online retailer in the United States.[4] As of March 2015, its website attracted 175 million visits per month (compared to 122 million and 82 million, respectively, for the websites of eBay and Wal-Mart, its two largest competitors).[5] Amazon also launched Auctions, an online auctions service, in March 1999, and zShops—a fixed-price marketplace business—in September 1999: these evolved into Amazon MarketPlace, a service launched in November 2000 that allows third-party sellers to sell their products directly to Amazon customers. This move made Amazon both retailer and platform provider. In 2013, Amazon had more than 2 million third-party sellers and they accounted for approximately 40% of Amazon's sales.[6] Amazon offers two free shipping programs: subscribers to Amazon Prime receive unlimited free two-day shipping on items sold or shipped by Amazon.com for an annual membership fee of $99; merchandise orders of at least $35 are typically delivered for free within five to nine business days under Amazon's Free Super Saver Shipping option.[7]

Several factors may increase Amazon's incentives to enter third-party sellers' product

[4]For more information about Amazon's performance in recent years, see, for example: Amazon.com. 2015. Amazon sellers sold record-setting more than 2 billion items worldwide in 2014. 5 January: `http://phx.corporate-ir.net/phoenix.zhtml?c=176060&p=irol-newsArticle&ID=2002794`, accessed, August 2015.

[5]Source: Statista.com. 2015. Most popular retail websites in the United States as of March 2015, ranked by visitors (in millions). *Statista Inc.* `http://www.statista.com/statistics/271450/monthly-unique-visitors-to-us-retail-websites/`, accessed August 2015.

[6]Source: Faggiano M. 2014. Fulfillment by Amazon: What Amazon doesn't tell third-party sellers. *Venture Beat.* 8 January: `http://venturebeat.com/2014/01/08/fulfillment-by-amazon-what-amazon-doesnt-tell-third-party-sellers/` , accessed August 2015.

[7]Source: Amazon.com. Amazon Prime and free shipping. `http://www.amazon.com/gp/help/customer/display.html?ie=UTF8&nodeId=200285890`, accessed August 2015. Starting in May 2015, Amazon allowed products from some merchants to qualify for Prime's free two-day shipping program without using Amazon's fulfillment service (see, for example: Del Ray J. 2015. Amazon relents on key merchant policy so Prime members can get better selection. *Re/code.* 14 May: `http://recode.net/2015/05/14/amazon-relents-on-key-merchant-policy-so-prime-members-can-get-better-selection/`, accessed August 2015).

spaces. First, having complete transaction data for third parties selling on its platform, Amazon can readily identify hit products or those whose performance Amazon could help improve.

Second, having been a retailer for many years itself, Amazon has the capabilities needed to resell third-party products with high-quality service, so the barrier to its entry would be low.

In addition, one risk of relying on third-party sellers to fulfill its customers' needs is that Amazon cannot entirely control the authenticity of their products and the quality of customer services. This lack of control can sometimes get Amazon into trouble, both with its customers and the product manufacturers.[8] Amazon may prefer selling products itself to mitigate such risks.

Finally, one would expect that after its entry, Amazon could easily promote such products on its own site, which would likely make it the single largest seller for these products. Selling large volumes of those products would give Amazon significant bargaining power with the product suppliers. Amazon could translate the lower costs at which it could obtain these products over third-party sellers into either higher profits or lower prices to consumers, the latter further increasing customer satisfaction.

Meanwhile, there are several factors that might reduce Amazon's incentives to enter third-parties' product spaces. First, Amazon already makes a profit from these sellers; for example, it receives referral fees from third-party sales ranging from 6%-45% of products' purchase prices, as well as charging larger sellers a monthly membership fee, but it might have to lose this income if it chose to compete against them.[9]

Second, Amazon generates revenues from third-party sellers through a service called

[8]Source: NG S, Rockoff J. 2013. Amazon and J&J Clash Over Third-Party Sales. *Wall Street Journal*. 10 November: `http://www.wsj.com/articles/SB10001424052702303460004579190270427483810`, accessed August 2015.

[9]Source: Amazon.com. Selling on Amazon fee schedule. `https://sellercentral.amazon.com/gp/seller/registration/participationAgreement.html`, accessed August 2015.

"Fulfillment by Amazon," which helps handle third-party sellers' back-end operations. To use this service, third-party sellers simply ship their inventory to Amazon, and pay Amazon for storage, weight handling, and pick & pack operations. Amazon then manages their entire back-end operations, including storage, customer order fulfillment, and customer service. These products also qualify for Amazon free shipping programs. While this service provides Amazon more data to optimize its entry strategy, because Amazon already handles most of the logistics for these products, direct entry would afford little opportunity to improve the quality of customer service for these products.

Finally, Amazon has established a reputation for sacrificing profits in favor of long-term growth.[10] It tries to keep prices on its core business below those of competitors and invests heavily in such diverse areas as online grocery, hardware devices, and cloud computing services.[11] Amazon's focus on long-term growth rather than short-term profits requires it to cultivate its relationship with third-party sellers to help them grow, rather than competing directly with them, and risking driving them onto competing platforms like eBay or Wal-Mart.

In sum, whether Amazon chooses to enter third-party sellers' product space, and if it does, which product spaces it is most likely to enter, are empirical questions. Many platform providers today face similar trade-offs in managing relationships with complementors (e.g., short-term profitability vs. long-term growth). Results from Amazon.com can help us better understand the incentives that influence platform providers' entry decisions with respect to complementors' market spaces.

[10] See, for example: Nasdaq. 2014. Amazon Is unprofitable — and it's completely on purpose. 25 July: `http://www.nasdaq.com/video/amazon-is-unprofitable---and-its-completely-on-purpose-518340934`, accessed August 2015.

[11] Source: The Guardian. 2014. What does Amazon care for losses? Its plan is for world domination. *The Guardian.* 26 July: `http://www.theguardian.com/technology/2014/jul/27/amazon-losses-falling-shares-world-domination-jeff-bezos`, accessed August 2015.

3 Data and Variables

We collect data from Amazon.com on four product categories and associated subcategories: (1) Electronics & Computers, (2) Home, Garden & Tools, (3) Toys, Kids & Games, and (4) Sports & Outdoors. In total, these four categories collectively accounted for approximately 58 million products as of June 2013. Categories like Books and Music are excluded, as products therein are offered primarily by Amazon.

We collect data in two rounds, first in June 2013 and then in April 2014.[12] We identify in the first round a set of products offered only by third-party sellers, and then, in the second round, check whether Amazon has entered these product spaces in the intervening period. As we cannot know *ex ante* which product spaces Amazon will choose to start selling itself, we need to collect information on as many products as possible in the first round. One challenge for collecting many data from Amazon is that Amazon bans an IP address for a few hours if it tries to access Amazon's pages too frequently. We try to circumvent this IP blockage by accessing Amazon via 30 different proxies and introducing a delay of several seconds after each access. Because of the large number of products Amazon offers, it is practically impossible to gather information from every product listed on Amazon. Thus, we design our program to check only 0.5% of products under each subcategory.

We obtain, for each product not offered by Amazon, price (*Price*), shipping cost (*Shipping*), average customer rating (*AverageRating*), and total number of sellers that offer the product in new condition (*NumSellers*). Note that many sellers may sell the same product on Amazon for different prices and shipping costs, so we obtain the price and shipping information from the default page Amazon displays when users search for the product. We also obtain the ID of the default seller, typically the one that offers the product at the lowest cost (i.e., price plus shipping cost), and capture whether the seller uses Amazon's fulfillment

[12] Our data collection procedure adheres to Amazon's robots exclusion protocol (available at `http://www.amazon.com/robots.txt`, accessed April 2014).

service using a dummy variable, *FulfilledByAmazon*, coded 1 if third-party product distribution is handled by Amazon, and 0 otherwise. Amazon does not publish sales data for each product, but does provide sales ranking data for products in each product category. Past research (e.g., Chevalier and Goolsbee 2003; Sun 2012) have identified a log-linear relationship between sales ranks and actual sales, so we obtain ranking information for each product (*SalesRank*). Rankings are negatively correlated with sales, a lower ranking indicating higher sales. Products out of stock or sold only in used condition are excluded. In total, we obtain product information for 163,853 products in 22 subcategories.

We also gather information on the total number of products offered on Amazon by each third-party seller (*NumProdBySeller*) in our data set as well as for a subset of these third-party sellers' other products including prices and whether they use Amazon's fulfillment service. As the number of products these third-party sellers offer varies between 1 and 15 million, it is not feasible to gather information about every such product; we therefore gather information on up to 40 products listed on the store page of each third-party seller.

For all products we gather in the first round, we gather the same set of information again in the second round. Of the 163,853 products identified in the first round as being offered only by third-party sellers, we find that Amazon has entered 4,852 (3%) of these product spaces between the two rounds. Table 1 provides the distribution of these products across subcategories for the whole sample and for those affected by Amazon's entry. We find the top four subcategories (Toys & Games, Sports & Outdoors, Electronics, and Home & Kitchen) to account for more than 88% of Amazon entries and the percentage of product entries in each subcategory to vary from 0 to 7.34%. We observe no entries in five subcategories (Computers & Accessories, Video Games, Software, Grocery & Gourmet Food, and Watches).[13]

[13]This pattern is likely to reflect Amazon's growth strategies in the past. For example, Amazon signed an agreement with Toys "R" Us in 2000 that gave Toys "R" Us the rights to be the sole seller of toys, games and baby products on Amazon. This partnership, which was supposed to last 10 years, did not go well and ended in 2006. As a result, Amazon may have delayed its own entry into product spaces under the Toys & Games category. Similarly, in 2001 Amazon partnered with Circuit City, a large electronics retailer then, but the

Table 2 presents summary statistics for the product spaces that Amazon has and has not entered, based on product information collected in the first round. We take logarithms of several variables that exhibit skewed distributions. Looking at product prices and shipping costs, we find that, on average, the products Amazon chooses to offer after the first round tend to have higher prices and lower shipping costs. The latter result is consistent with the explanation that, as Amazon offers free shipping through its prime or super saver shipping programs, it does not want to enter the spaces of products that require high shipping costs (e.g., bulky items).

We look next at the products' sales rankings and average consumer ratings. Because not all products have consumer reviews, we compute average ratings only for products with at least one review. If Amazon's entry is motivated by capturing profits from popular products, we expect Amazon to pick those with low rankings (i.e., high demand) and high customer ratings. On the other hand, if Amazon is seeking to help improve customer experience by entering third-parties' low-performing products, we expect it to pick products with high rankings and low ratings for its entry. Our evidence supports the former explanation, that is, that Amazon is more likely to pick lower ranked (i.e., more popular) and higher rated products (i.e., greater customer satisfaction).

We next look at the likelihood of a third-party product being distributed by Amazon. When a product is distributed by Amazon, the platform generates additional profits from this service from these sellers, in addition to a percentage of sales revenue. Because consumers who purchase these products already benefit from Amazon's high-quality distribution service, there is little room to improve customer experience by direct entry. Whether entry is motivated by profits or the desire to improve the customer experience, the likelihood of entry should be lower for third-party products distributed by Amazon. On the other hand,

relationship ended in 2005. Source: Mangalindan M. 2006. How Amazon's dream alliance with Toys "R" Us went so sour. *Wall Street Journal.* 23 January: http://www.wsj.com/articles/SB113798030922653260, accessed August 2015.

Amazon's additional information advantage from fulfilling these products (e.g., knowledge of inventory space requirements, the suppliers from which they are sourced, etc.) should facilitate, and thereby increase the likelihood of, entry. The summary statistics show that Amazon is more likely to enter the spaces of products that use its distribution service.

We also look at the number of sellers offering that product. When a large number of sellers offer same product, the intensity of competition may reduce Amazon's incentive to enter. On the other hand, a large number of sellers suggest that sourcing the product is easy, which might increase the likelihood of Amazon's entry. We find that on average, Amazon is more likely to enter spaces of products offered by many sellers, suggesting that convenience of sourcing dominates competitive effects.

Lastly, we examine the total number of products default third-party sellers offer on Amazon. On one hand, Amazon may strategically avoid squeezing large third-party sellers because they are important for value creation, but in probabilistic terms, products by big sellers are more likely to become targets of entry by Amazon. We find that products affected by Amazon's entry tend to be those offered by bigger sellers, suggesting that avoiding big sellers is not a strong incentive when Amazon chooses which products to offer itself.

The significant differences observed in Table 2 between the product spaces Amazon chooses to enter and not to enter suggest that its entry decisions are not random. Amazon is more likely to target for entry products that are popular and have good reviews.

4 Empirical Analysis

4.1 Amazon's Entry Pattern

We explicitly model Amazon's entry pattern in a regression framework. Many of the variables in Table 2 are correlated—for example, products with good reviews or fulfilled by Amazon are also likely to be popular (i.e., have low rankings)—so it is important to conduct multivariate regression analysis to gain robust insights into Amazon's entry pattern.

Table 3 reports logit regression results from which we try to identify Amazon's entry pattern. We include all products offered only by third-party sellers from the first round data collection. The dependent variable is a dummy, *Entered*, which is 1 if Amazon offers the product in the second round by itself, and 0 otherwise. Model (1) includes product information such as prices, shipping costs, and sales rankings, and we add the customer ratings in Model (2). Because not all products have consumer reviews, we include, instead of average consumer ratings, dummy variables for different product rating levels. The benchmark group consists of products with no ratings. We also include information on whether the product is fulfilled by Amazon and the logarithm of the total number of third-party sellers offering the same product. In Model (3), we add as additional controls dummies for product categories, and in Model (4), the logarithm of the total number of products offered by the third-party sellers.

We find, in all four models, that entry by Amazon is more likely for products with higher prices, lower shipping costs, and greater demand. We also find, from the coefficients of the product rating dummies, that Amazon's likelihood of entry increases with a product's customer rating. Interestingly, in contrast to summary statistics in Table 2, we find, when controlling for various co-variants, that Amazon is less likely to enter a product space of a third-party seller that uses Amazon's distribution system. We also find that Amazon is more likely to enter product spaces when the number of third-party sellers is large, and that it does not seem deterred by the size of third-party sellers. Overall, these results are consistent with the view that Amazon's entry is motivated primarily by its desire to capture more value.

4.2 Impact of Entry on Third-Party Products

We next evaluate the impact of Amazon's entry on third-party products. Because the product spaces Amazon enters are not chosen at random, we cannot simply compare affected to unaffected products to evaluate the impact of Amazon's entry. We first use data from the first round to conduct propensity-score matching. With propensity-score matching, for each affected product, we use the first-round data to identify an unaffected product that is very similar to it except that this product has not been affected by Amazon's entry during our study period (it is possible that the unaffected product became affected by Amazon's entry after our study period). We can then identify the impact of Amazon's entry by using the second-round data to compare the affected products (treatment group) to their matched unaffected counterparts (control group). We use Model (4) from Table 3 to generate the propensity scores that we use to find matches for the affected products.[14] Because we have a large number of unaffected products, all affected products are matched with unaffected products during matching, except one.

Table 4 presents the results. First, we look at the products' prices on Amazon. For those that Amazon has entered, their prices are determined by Amazon. We find that the prices for the products affected by Amazon's entry in the second period are not statistically different from those it does not enter.

We also compare their shipping fees. As Amazon offers free shipping programs (via its prime and super saver deals), when Amazon offers products, their shipping fees become zero. Although third-party sellers have the option of offering free shipping for their products or using Amazon's distribution to take advantage of its free shipping offers, third-party sellers' shipping fees are, on average, significantly higher.

Examining their sales rankings, we find demand in the second round to be greater for products Amazon started selling itself than for products in the control group. This is not surprising, as Amazon's lower shipping costs decrease the overall costs of these products to consumers. Interestingly, we do not find significant differences between the average customer ratings of affected and unaffected products, suggesting that Amazon's entry does not seem

[14] We perform the matching using the single nearest-neighborhood algorithm with a caliper of 0.01.

to increase consumer satisfaction with the products.

Lastly, we examine the likelihood of third-party sellers continuing to offer, in the second round, products entered by Amazon. Reduced demand consequent to Amazon's entry could discourage third-party sellers from continuing to sell the affected products. On the other hand, subsequent to Amazon's entry, it may take some time for these sellers to reduce inventories accumulated while being the default sellers, in which case the products may continue to by offered by the third-party sellers. We create a dummy, *StopOffer*, which is 1 if the seller ceases to offer a product in the second, and 0 otherwise. We find the turnover rate for product offerings by third party sellers between the first and second rounds to be generally quite high, exceeding 40% for both affected and unaffected products. The likelihood of these products no longer being offered by the same third-party sellers in the second round is six percentage points higher for products affected than for products unaffected by Amazon's entry.

Overall, our results suggest that Amazon's entry reduces the shipping cost—and hence the cost to consumers—of affected products, resulting in increased sales of these products, but it also discourages third-party sellers from continuing to offer the products.

4.3 Impact of Entry on Third-Party Sellers

We examine the impact of Amazon's entry on third-party sellers by comparing shifts in behavior between sellers affected and those unaffected by Amazon's entry. We identify affected sellers from those whose products are affected, and unaffected sellers from the control group. Because our matching is conducted at the product level, it is possible that the same seller has affected products in the treatment group and unaffected products in the control group, and so we drop all sellers that show up in both groups.[15] Our final data set consists of 966 affected, and 1,544 unaffected, sellers. Because multiple products of the same seller may

[15] Our results do not change qualitatively if we include these sellers as affected sellers.

be affected by Amazon's entry, we compute, for each seller, *NumEntered*, being the total number of products offered by the seller that are affected by Amazon's entry. For unaffected sellers, this variable has a value of 0; for affected sellers, on average, each has 1.61 products that are impacted by Amazon's entry (ranging from 1 to 28).

Because our propensity-score matching, performed at the product level, does not account for attributes of pre-existing differences among these sellers, we use a "difference-in-differences" approach together with seller-fixed effects to examine shifts in sellers' strategies. We create two dummy variables *Affected*, which is 1 if the seller is affected by Amazon's entry and 0 otherwise, and *After*, which is 0 if it is the first round and 1 otherwise.

We first examine changes in the total number of products offered by third-party sellers over the two periods in Panel A. The dependent variable, *Log(NumProdBySeller)*, is the logarithm of the total number of products offered by a third-party seller in each round. We include as independent variables *After* and its interaction with *Affected*. Because we control for seller-fixed effects, the main effect of *Affected* is absorbed. Model (1) of Panel A shows our result. Our finding that the interaction variable is negative and significant suggests that affected sellers are more likely than unaffected sellers to reduce the numbers of products they offer on Amazon. Model (2), in which we replace the variable *Affected* with *Log(NumEntered)* to better capture the heterogenous impact of Amazon's entry on these sellers, yields similar results. As large sellers may behave differently from small sellers, in Models (3)-(6), we repeat the analyses in Models (1)-(2) for large sellers and small sellers, respectively. We define a seller as a large (small) seller if it offers more (fewer) products than the median number of products offered by all sellers in the first round. We find that the effect is greater and more significant for small sellers.

We next examine changes in seller behavior at the individual product level using data collected on other products offered by these sellers in Panels B and C of Table 5 . We thus control for product-level fixed effects in these two panels. For those products that continue to be offered by the third-party sellers in the second round, we examine shifts in sellers' strategies regarding whether or not to use Amazon's distribution channels, as captured by *FulfilledByAmazon*. Some sellers stopped offering the products we collect data for in the first round, so we drop them from the analyses. Although our dependent variable is binary, we use linear probability models to facilitate interpretation of the interaction variables.[16] The results in Table 3 seem to imply that sellers' rational response to forestall entry by Amazon would be to start using its distribution system. On the other hand, sellers adversely affected by Amazon's entry may be discouraged from developing closer relationships with the platform. We replicate the analysis in Panel A and report the results in Panel B. We find that, consistent with the latter explanation, Amazon's distribution system is less likely to be used by affected third-party sellers than by sellers in the control group. We also find that this effect is only significant for large sellers, and the magnitude of the effect appears to be small. The result suggests that the primary response for small sellers is to carry fewer products, rather than adjust their inventory strategies.

We examine how Amazon's entry affects third-party sellers' pricing strategies. The dependent variable is the logarithm of the product prices. Our results reported in Panel C reveal no significant shifts in sellers' pricing strategies for both large and small sellers.

Overall, the results reported in Table 5 suggest that when affected by Amazon's entry, third-party sellers, particularly small ones, are discouraged from growing their businesses on the platform.

4.4 Robustness Checks

We conduct a few robustness checks to ensure that our conclusions are not driven by alternative explanations and report the results in Table 6. First, Amazon's entry decision is

[16] In our analysis, 100% of the predicted probabilities lie between zero and one. Angrist and Pischke (2008) and Horrace and Oaxaca (2006) show that in such cases, linear probability models with robust standard errors yield unbiased and consistent estimates.

likely to depend on some unobservables. The platform may not, for example, be able to enter the product space of a manufacturer that sells its product directly on Amazon (e.g., Dumrongsiri et al. 2008). Although the information on Amazon.com does not allow us to identify products sold directly by manufacturers, repeating the analysis excluding products sold by only one third-party seller yields similar results (Model (1) of Table 6).

Second, our logit regressions implicitly assume that entry probability is primarily correlated to product characteristics rather than seller characteristics. To confirm this assumption, we add third-party sellers' ratings in the logit regressions. The rating of each seller is computed as the average of all ratings the seller receives from its past transactions, and captures the seller's service quality instead of quality of his or her products. The rating is likely to be correlated to variables such as *Price*, *Shipping*, and *FulfilledByAmazon*: Sellers with greater service quality are likely to command higher prices; they are also likely to use Amazon's fulfillment services or have efficient distribution systems themselves, both resulting in lower shipping costs. If Amazon's entry decisions are not orthogonal to seller ratings, inclusion of seller ratings is likely to have a large impact on the magnitude and significance of current predictors. Model (2) of Table 6 reports results after including seller ratings. Only 27 products are sold by sellers with ratings between 1 and 3 and for all these products, we observe no entry. As a result, these observations are dropped during estimation due to lack of variation. We find that seller ratings have no influence on entry probability. Moreover, after including seller ratings, the results for other variables are virtually unchanged from those in Model (4) of Table 3, although we expect seller ratings to be correlated with several other variables. The result thus confirms our empirical assumption and boosts confidence in our empirical approach.

Third, special contractual agreements with large, third-party sellers may reduce the like liho cod of entry by Amazon. We drop top 10% of the third-party sellers based on the total number of products they carry in the first round and repeat the analysis. We continue to find similar results (Model (3) of Table 6).

Finally, although our logit regression includes a large number of product characteristics, it is possible that Amazon's entry decisions depend on other unobservables. Amazon may, for example, look at growth in product sales instead of current sales figures. While our conclusion that Amazon selects more promising product spaces to enter continues to hold in such cases, we take three approaches to examine robustness. First, we exclude five product subcategories (Toys & Games, Electronics, Computers & Accessories, Video Games, and Software) in which products are likely to exhibit significant trends. For the remaining product subcategories, as new products are likely to exhibit great demand variation, we exclude all products that became available on Amazon.com after January 1, 2013. Demand for the remaining products in our data set is likely to be relatively stable. Repeating the logit regression with these products reveals a similar entry pattern (Model (4) of Table 6). The influence of several variables like our rating variables and *FulfilledByAmazon* become greater.[17]

We also test the sensitivity of our results from propensity-score matching by estimating Rosenbaum bounds (Rosenbaum 2002; Leuven and Sianesi 2003), which measure how strong an influence an unobservable factor must have on the selection process to nullify the identified causal effects from the propensity-matching analysis.[18] We find that, depending on the outcome variable, an unobservable variable would have to change the odds of selection into the treatment group by an amount ranging from 30% to more than 100% for the significant treatment effects in Table 4 to disappear.[19] In addition, these thresholds are conservative estimates and hence any confounding unobservable would need to have an extremely high,

[17]Replicating, in unreported regressions, the analyses in Tables 4 and 5 yields similar results.

[18]If we label the probability of a product being in the treatment group p_i, and the probability of the matched product being in the control group p_j, Rosenbaum (2002) gives the bounds on the odds ratio for the products being matched as: $\frac{1}{\Gamma} \leq \frac{p_i/(1-p_i)}{p_j/(1-p_j)} \leq \Gamma$, where $\Gamma \geq 1$. Based on the intuition that Γ should be close to 1 if the unobservable does not play a significant role in selection, Rosenbaum develops test statistics to show how far Γ must be from 1 for the unobservable to nullify the treatment effect.

[19]Note that the threshold we find is on the same order of magnitude as the Rosenbaum bounds results reported by DiPrete and Gangl (2004) and Sen et al. (2011).

almost deterministic influence on selection into the treatment group and our outcome variables (DiPrete and Gangl 2004). Hence, the effect of Amazon's entry on affected products and sellers is unlikely to be negated by factors unobserved in our study.

5 Discussion and Conclusion

Our research provides the first large-scale empirical study of co-opetition between platform owners and complementors using data from Amazon.com, and highlights the importance for complementors of taking value capture into account when building businesses on platforms. As platform owners are often strategic players, complementors need to understand the incentives and capabilities of platforms and not treat platform-based markets as regular markets.

Just like any other empirical studies, one may worry whether the entry pattern we have documented merely reflects coincidence: Amazon could have used an independent process to identify these products to source by itself instead of using data about third-party products. Although this possibility is hard to rule out without direct observations of Amazon's operations, several indications suggest that the entry pattern is beyond sheer coincidence. First, in our logit regressions, if Amazon's merchandise planning process is completely independent of data related to third-party products, the dummy variable, *FulfilledByAmazon*, should not be highly significant in all specifications. Second, interviews by Brad Stone with current and former Amazon executives suggest that Amazon indeed uses its Marketplace as a learning tool to decide whether it should get into certain product markets (Stone 2013). For example, according to Stone (2013), Randy Miller, the former Director of Merchandise Planning at Amazon, said "If you don't know anything about the business, launch it through the Marketplace, bring retailers in, watch what they do and what they sell, understand it, and then get into it" (Stone 2013, p. 182). Our research thus complements the field interviews by examining the extent of Amazon's entry, product spaces Amazon is more likely to target, and the impact of entry.[20]

While our research focuses on Amazon.com as the empirical setting, our results have implications for complementors participating in many different platform-based markets. We show that, although Amazon cares about its long-term growth, it still has incentives to appropriate value from third-party sellers selling successful products on its platform. As a result, the appropriation risks would be even higher for complementors when they work with platform owners that focus on short-term profit maximization.

Our results also inform complementors' strategies in different platform-based markets, and highlight factors that do and do not influence platform owners' incentives to squeeze complementors out of the market. We find, for instance, contrary to the conventional wisdom that firms typically find competitive markets unattractive for entry (e.g., Berry and Reiss 2007), that intensity of competition among complementors does not seem to affect platform owners' entry decisions. In our setting, we observe across many instances of Amazon entry that Amazon may present itself as the default seller even when third-party sellers' products are offered at lower cost (i.e., product price plus shipping cost) with comparable shipping speeds, and these third-party sellers have high ratings. Although Amazon sometimes notes on its product pages that products may be offered at lower cost by third-party sellers, even consumers who notice this message (and many likely don't) may not be disposed to spend time examining the list of third-party sellers. Competition thus does not seem to influence Amazon's choice of products to offer: after all, third-party sellers will be competing with Amazon on its web site under its rules. Similar scenarios take place in other settings. Applications supplied by platform owners (e.g., Microsoft and Apple), for example, are

[20]Note that our research does not imply that individuals in charge of obtaining new merchandises at Amazon must have access to detailed transaction data for third-party products. As Amazon publishes data related to third-party products on its website (e.g., consumer reviews and product ranks), they can simply browse Amazon.com to obtain such information.

often bundled with their respective platforms (e.g., Windows and iOS). Unbundled rival complementary products consequently are handicapped by the extra cost consumers need to incur acquiring, searching for, and installing them. In the end, consumers may opt for platform owners' copycats even when the quality is inferior to complementors' original innovations.

While our results may paint a gloomy picture for complementors in various platform-based markets, they do suggest several strategies complementors can use to mitigate the risk of being squeezed. Complementors might, for example, focus on products platform owners do not want to sell. As platforms tends to target popular products, complementors that build their businesses around aggregating non-blockbuster products or services (e.g., Zentner et al. 2013) are less likely to face direct competition from platform owners.

Complementors can also seek ways to impede entry by platform owners. In our setting, third-party sellers can try to sign exclusive contracts with manufacturers to be the sole suppliers of certain products, or try to conceal their suppliers' information from Amazon. They may also choose to manufacture some complementary products on their own. In other markets, complementors may use patents to protect their innovations.

Finally, complementors may choose to share more value with platform owners to reduce their incentives to enter. Our results show, for example, that complementors' use of Amazon's fulfillment services reduces the likelihood of its entry. In other settings, sometimes platform owners enter complementary markets because complementors limit platform owners' ability to monetize their services. For example, Twitter released its own client app to compete with third-party client apps because owning the client app helped it monetize its service.[21]

Although Amazon's entry can harm complementors and may potentially reduce the number of innovative products consumers can find on the site, our results show that such entry

[21] See, for example: Flip the Media. 2008. To tweet, perchance to monetize. 22 October: `http://flipthemedia.com/2008/10/1593/` and Twitip. 2010. Twitter takes control over client apps - good or bad?. 15 April: `http://www.twitip.com/twitter-takes-control-over-apps/`, accessed August 2015.

can allow consumers to benefit from Amazon's efficient distribution systems, and that they are more likely to purchase the products. Hence, consumer welfare may actually increase—so the overall social welfare effect of platform owner entry in this case is not clear.

Future research could extend our study in various directions. Our study, for example, involves a setting in which it is difficult for complementors to deter entry by the platform owner. In platform markets like the software industry, complementors may be able to employ defense mechanisms such as patents to protect their innovations (e.g., Wen et al. 2013). Consistent with this logic, Huang et al. (2013) find that software firms with a greater stock of patents and copyrights are more likely to join SAP's platform. Acquisition may be the only avenue open to platform owners seeking to enter the product spaces of complementors with strong defense mechanisms. Li and Agarwal (2015) study Facebook's acquisition of Instagram, a popular photo-sharing application, and show that this move expands demand for the latter by attracting new users who previously did not use any photo-sharing applications. The result mirrors our finding that Amazon's entry increases the popularity of affected products. Future research could assess the generalizability of our results to other settings in which platform owners use different entry strategies.

Data limitations prevent our study from examining how Amazon's entry strategies affect its growth. Current or potential complementors discouraged by Amazon's entry may bring fewer innovative products to the platform. But if Amazon's entries attract more consumers and lower the cost of offered products, the expanded consumer base could incentivize more third-party sellers to join the platform. Thus, how Amazon's direct competition against its complementors affects platform growth remains an open question.

Finally, complementors should be aware that, although the most threatening and visible form of squeezing, direct entry into their product spaces is not the only approach available to platforms for appropriating value from complementors' innovations (e.g., Edelman 2014). For example, being purely a marketplace, eBay has not developed the capability to operate as a retailer and so is not positioned to compete directly with third-party sellers. But eBay has increased its service fees several times to capture more value from its sellers. Apple often uses terms and conditions to reject applications that compete directly with its own offerings. Facebook reduced the number of game posts from Zynga, a large third-party game publisher, on its newsfeed, which weakened Zynga.[22] Future research could explore how platform owners employ different strategies to squeeze complementors.

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Table 1: Distribution of Products Across Subcategories

	All Products		Affected	
Subcategory	Freq.	% of All Products	Freq.	% of Products
Toys & Games	63,335	38.65	2,288	3.61
Sports & Outdoors	31,955	19.50	1,052	3.29
Home & Kitchen	26,141	15.95	730	2.79
Electronics	23,081	14.09	328	1.42
Baby	3,389	2.07	87	2.57
Home Improvement	3,136	1.91	79	2.52
Health & Personal Care	2,777	1.69	36	1.30
Office Products	1,985	1.21	56	2.82
Patio, Lawn & Garden	1,636	1.00	40	2.44
Pet Supplies	1,405	0.86	18	1.28
Automotive	1,396	0.85	30	2.15
Kitchen & Dining	1,093	0.67	25	2.29
Industrial & Scientific	866	0.53	26	3.00
Arts, Crafts & Sewing	456	0.28	29	6.36
Beauty	410	0.25	6	1.46
Computers & Accessories	306	0.19	0	0.00
Musical Instruments	286	0.17	21	7.34
Video Games	89	0.05	0	0.00
Appliances	56	0.03	1	1.79
Software	45	0.03	0	0.00
Grocery & Gourmet Food	8	0.00	0	0.00
Watches	2	0.00	0	0.00
Total	**163,853**	100.00	**4,852**	**2.96**

Table 2: Comparison of Products Affected and Unaffected by Amazon's Entry

	Affected				Unaffected				
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean Difference
Log(Price)	3.06	1.11	0.01	7.70	2.92	1.18	0.01	9.71	0.14***
Log(Shipping)	0.65	0.97	0.00	5.03	0.88	1.02	0.00	6.29	-0.22***
Log(SalesRank)	10.76	2.07	0.00	15.15	11.55	2.24	0.00	15.15	-0.79***
AverageRating	4.24	0.75	1.00	5.00	4.18	0.88	1.00	5.00	0.06***
FulfilledByAmazon	0.40	0.49	0.00	1.00	0.31	0.46	0.00	1.00	0.09***
Log(NumSellers)	1.84	1.08	0.00	5.60	1.31	1.10	0.00	5.55	0.53***
Log(NumProdBySeller)	7.88	2.00	0.00	16.49	7.52	2.03	0.00	16.49	0.36***

Note: The last column includes the mean difference with its significance from a two-tailed t-test. *** significant at 1%.

Table 3: Logit Regressions for Analyzing Amazon's Entry Pattern

Variables	(1)	(2)	(3)	(4)
Log(Price)	0.112***	0.136***	0.230***	0.254***
	(0.011)	(0.011)	(0.013)	(0.013)
Log(Shipping)	−0.185***	−0.088***	−0.105***	−0.101***
	(0.016)	(0.019)	(0.018)	(0.019)
Log(SalesRank)	−0.119***	−0.084***	−0.133***	−0.143***
	(0.004)	(0.005)	(0.008)	(0.008)
$1 \leq$ AverageRating < 2		−0.230	−0.189	−0.166
		(0.149)	(0.149)	(0.149)
$2 \leq$ AverageRating < 3		−0.002	0.030	0.076
		(0.091)	(0.091)	(0.091)
$3 \leq$ AverageRating < 4		0.135***	0.167***	0.217***
		(0.051)	(0.051)	(0.052)
$4 \leq$ AverageRating ≤ 5		0.252***	0.213***	0.251***
		(0.037)	(0.037)	(0.037)
FulfilledByAmazon		−0.142***	−0.192***	−0.082**
		(0.038)	(0.038)	(0.039)
Log(NumSellers)		0.353***	0.350***	0.323***
		(0.013)	(0.015)	(0.015)
Log(NumProdBySeller)				0.123***
				(0.008)
Dummies for Categories	No	No	Yes	Yes
Observations	163,853	163,853	163,853	163,853
Pseudo R-squared	0.02	0.03	0.05	0.05

Note: Heteroskedasticity-adjusted standard errors are in parentheses. ** significant at 5%; *** significant at 1%.

Table 4: Impact of Amazon's Entry on Third-Party Products

Variable	Treated	Controls	Difference	S.E.	T-stat
Log(Price)	3.09	3.06	0.02	0.02	0.91
Log(Shipping)	0.00	0.57	-0.57	0.01	-39.80***
Log(SalesRank)	10.23	11.09	-0.86	0.05	-17.64***
AverageRating	4.21	4.21	0.00	0.02	-0.14
StopOffering	0.50	0.44	0.06	0.01	6.11***

Note: *** significant at 1%.

Table 5: Impact of Amazon's Entry on Third-Party Sellers

Panel A: Number of Products Carried by Third-Party Sellers

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		Large Sellers		Small Sellers	
Variables	Log(NumProdBySeller)	Log(NumProdBySeller)	Log(NumProdBySeller)	Log(NumProdBySeller)	Log(NumProdBySeller)	Log(NumProdBySeller)
After	−0.203***	−0.239***	−0.365***	−0.409***	−0.021	−0.055
	(0.044)	(0.042)	(0.069)	(0.067)	(0.050)	(0.049)
Affected × After	−0.285***		−0.276**		−0.341***	
	(0.077)		(0.127)		(0.089)	
Log(NumEntered) × After		−0.220***		−0.165		−0.309***
		(0.075)		(0.113)		(0.095)
Observations	5,020	5,020	2,512	2,512	2,508	2,508
R-squared	0.034	0.032	0.051	0.049	0.024	0.020
Number of Sellers	2,510	2,510	1,256	1,256	1,254	1,254
Specifications	FE	FE	FE	FE	FE	FE

Panel B: Use of Amazon's Fullfillment Service

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		Large Sellers		Small Sellers	
Variables	FulfilledByAmazon	FulfilledByAmazon	FulfilledByAmazon	FulfilledByAmazon	FulfilledByAmazon	FulfilledByAmazon
After	−0.001	−0.002	0.020***	0.018***	−0.031***	−0.031***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Affected × After	−0.015***		−0.021***		0.001	
	(0.003)		(0.003)		(0.005)	
Log(NumEntered) × After		−0.012***		−0.017***		−0.001
		(0.003)		(0.003)		(0.005)
Observations	122,108	122,108	68,428	68,428	53,680	53,680
R-squared	0.001	0.001	0.003	0.002	0.006	0.006
Number of Products	61,054	61,054	34,214	34,214	26,840	26,840
Number of Sellers	2,212	2,212	1,120	1,120	1,092	1,092
Specifications	FE	FE	FE	FE	FE	FE

Panel C: Product Prices Set by Third-Party Sellers

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		Large Sellers		Small Sellers	
Variables	Log(Price)	Log(Price)	Log(Price)	Log(Price)	Log(Price)	Log(Price)
After	−0.012***	−0.015***	−0.006**	−0.009***	−0.020***	−0.023***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
Affected × After	−0.005		−0.001		−0.006	
	(0.003)		(0.004)		(0.005)	
Log(NumEntered) × After		0.003		0.006		0.000
		(0.003)		(0.003)		(0.005)
Observations	122,108	122,108	68,428	68,428	53,680	53,680
R-squared	0.001	0.001	0.000	0.000	0.003	0.003
Number of Products	61,054	61,054	34,214	34,214	26,840	26,840
Number of Sellers	2,212	2,212	1,120	1,120	1,092	1,092
Specifications	FE	FE	FE	FE	FE	FE

Note: The unit of observation is at the seller level in Panel A and at the product level in Panels B and C. Heteroskedasticity-adjusted standard errors are in parentheses. ** significant at 5%; *** significant at 1%.

Table 6: Robustness Checks of Amazon's Entry Pattern

Variables	(1) Remove NumSellers = 1	(2) Add Seller Ratings	(3) Remove Large Sellers	(4) Remove Products Exhibiting Trends
Log(Price)	0.237***	0.254***	0.222***	0.221***
	(0.014)	(0.013)	(0.018)	(0.019)
Log(Shipping)	−0.110***	−0.100***	−0.146***	−0.116***
	(0.021)	(0.019)	(0.026)	(0.025)
Log(SalesRank)	−0.130***	−0.143***	−0.149***	−0.211***
	(0.009)	(0.008)	(0.011)	(0.014)
$1 \leq$ AverageRating < 2	−0.152	−0.166	−0.257	−0.170
	(0.155)	(0.149)	(0.210)	(0.266)
$2 \leq$ AverageRating < 3	0.008	0.076	0.103	0.204
	(0.097)	(0.091)	(0.116)	(0.148)
$3 \leq$ AverageRating < 4	0.157***	0.216***	0.145**	0.480***
	(0.055)	(0.052)	(0.069)	(0.080)
$4 \leq$ AverageRating ≤ 5	0.192***	0.251***	0.265***	0.564***
	(0.040)	(0.037)	(0.051)	(0.060)
FulfilledByAmazon	−0.097**	−0.082**	−0.214***	−0.249***
	(0.041)	(0.039)	(0.051)	(0.059)
Log(NumSellers)	0.292***	0.322***	0.323***	0.411***
	(0.018)	(0.015)	(0.020)	(0.025)
Log(NumProdBySeller)	0.116***	0.121***	0.068***	0.109***
	(0.008)	(0.008)	(0.015)	(0.011)
$3 \leq$ AverageSellerRating < 4		0.156		
		(1.028)		
$4 \leq$ AverageSellerRating ≤ 5		0.184		
		(0.152)		
Dummies for Categories	Yes	Yes	Yes	Yes
Observations	119,894	163,826	111,755	76,693
Pseudo R-squared	0.04	0.05	0.04	0.07

Note: Heteroskedasticity-adjusted standard errors are in parentheses. ** significant at 5%; *** significant at 1%.