Competing with Complementors: An Empirical Look at Amazon.com*

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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 entries 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. Amazon's entry reduces the shipping costs of affected products and hence increases their demand. Results also show that third-party sellers affected by Amazon's entry appear to be discouraged from growing their businesses on the platform subsequently.

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 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. These platforms have spawned thousands of entrepreneurs who build their businesses on such platforms and sell their products or services to platform users. Collectively, these entrepreneurs—who operate as complementors to the platforms—create significant value. For example, by the end of 2014, more than 1.7 million applications and 1.4 million applications have been developed for Google's Android and Apple's iOS, two popular smartphone platforms, generating billions of dollars of revenue to each platform owner.[1]

At the same time, platform owners often have 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 as a result of 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 effectively extinguished by Microsoft's own rival applications, Internet Explorer and Windows Media Player; the microblogging platform Twitter released its own client applications for mobile devices and completely locked out client applications offered by third-party developers; and Apple makes some previously essential third-party apps obsolete with every new oper-

[1] Source: `http://tinyurl.com/lhy5x64`, accessed March 2015.

ating 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 relationship suggests that interdependence between firms may expose firms to value misappropriation risks, especially young firms who both have high resource needs and whose innovations are of high value (e.g., Katila et al. 2008; Diestre and Rajagopalan 2012; 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. They are typically small relative to the platforms, and often lack adequate resources to protect their innovations. In a similar vein, the literature on co-opetition has long held that companies in an industry may act as collaborators when it comes to value creation, but then become competitors when it comes to value capture (e.g., Brandenburger and Nalebuff 1997). In platform-based markets, one strategy for platforms to capture more value or limit the bargaining power of complementors is to imitate their successful products, and so appropriate value from their innovations.

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. By entering their product spaces a platform sends signals to current and potential complementors that they may not, in the end, be able to capture any value from their innovations. Consequently, current complementors may switch to other platforms, and potential complementors may not choose to affiliate with that platform. Consistent with these arguments, Iansiti and Levien (2004) point out that platforms need to work proactively to maintain the health of

[2]See, for example, `http://www.businessinsider.com/mountain-lion-apps-2012-7?op=1`, accessed November 2014.

[3]See, for example, `http://tinyurl.com/m8mbu7m` and `http://tinyurl.com/m7tnonq`, accessed November 2014.

their entire ecosystem, for a simple reason: their own survival depends on it. Gawer and Henderson's (2007) detailed case study of Intel's experiences with complementary markets in the PC industry shows how it uses organizational structure and processes as commitment mechanisms to convince its complementors that it will refrain from entering their markets. Gawer and Cusumano (2002) point out that Intel only 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 towards complementary markets. While there have been a few high-profile examples, it is 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 complementors to appropriate value from their innovations, or do they target underperforming complementors, 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?

In this research, we seek to answer these questions using data from Amazon.com, which is both the largest online retailer in the United States, and also a platform on which third-party sellers can sell their products directly to their customers. We examine the pattern of Amazon's entries into third-party sellers' product spaces. This empirical setting allows us to analyze systematically a platform owner's incentives to enter (or not to enter) a wide range of complementary product spaces. 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 these 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. We use propensity-score matching to

compare products affected by Amazon's entry to those unaffected, and find that Amazon's entry increases product demand because it reduces shipping costs to consumers. At the same time, 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. First, 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 their markets (e.g., Rochet and Tirole 2003; Parker and Van Alstyne 2005; Hagiu 2006; Seamans and Zhu 2014), interactions between competing platforms (e.g., Armstrong 2006; Economides and Katsamakas 2006; Casadesus-Masanell and Llanes 2011), how installed bases can constitute valuable resources to help platform owners diversify their businesses into other markets (e.g., Eisenmann et al. 2011; Edelman forthcoming), how platform owners should manage complementors (e.g., Yoffie and Kwak 2006; Parker and Van Alstyne 2014), when new platform owners can most successfully enter a platform-based market (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 limiting the variety of applications (Casadesus-Masanell and Halaburda 2014). The few extant studies on complementors tend to focus on the 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).

Our paper also relates to the literature on inter-organizational relationships, much of which again emphasizes positive outcomes for firms involved in such ties (e.g., Eisenhardt and Schoonhoven 1996; Rothaermel 2001, 2002; Gulati and Higgins 2003; Gulati et al. 2009) and the role of hub firms in creating value in inter-organizational networks (e.g., Kapoor and

Lee 2013). Consistent with resource dependence theory's identification of interdependence as the key motivation for tie formation (e.g., Ozcan and Eisenhardt 2009), these studies often find that complementors are more likely to form ties with dominant platform owners. The few studies in the inter-organization literature that explore the potential problems of value misappropriation—known as the 'swimming with sharks' dilemma—largely focus on whether small firms should form 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). While all these studies find that there are tensions between small firms' resource needs and the risk of value misappropriation, they do not address value misappropriation problems 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 setting also differs from conventional supply chains. For example, while merchants such as CVS, one of the largest pharmacy chains in the United States, buy products from their suppliers and then resell them to consumers, they may choose to offer their private labels to compete with their suppliers' (e.g., CVS produces its private labels to compete against national brands). In such cases, CVS bears all the cost of experimentation (e.g., promotion cost and logistics cost). In the platform setting, complementors bear the cost of experimentation for their products. They devote efforts into discovering innovative and interesting products to offer on the platforms and in many cases, the platform owners often would not have thought about selling certain products on their platforms without complementors' bringing these products to their attention. They often pay platform owners to promote these products. For example, many third-party sellers pay Amazon to advertise their products on Amazon.com. Therefore, complementors in platform-based markets create substantially more value than upstream suppliers in supply chains. Another difference is that merchants' entry with their own private labels do not typically push their suppliers out of the market. The extant research on merchants' entry into suppliers' product spaces typi-

cally finds that merchants' products are of lower quality and in equilibrium, both products co-exist by targeting consumer segments with different price sensitivities (e.g., Chintagunta et al. 2002; Steenkamp and Kumar 2007; Yehezkel 2008).

Finally, our paper relates to the literature on co-opetition (Brandenburger and Nalebuff 1997), which describes situations in which two firms are incentivized to work together to maximize the value of their joint product, but then compete in extracting profit from that product. 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. Amazon's direct entry into third-party sellers' product spaces is one way in which it can capture more of the value it creates jointly with third-party sellers. The relationships in our setting differ from that between Intel and Microsoft, in that one side (Amazon) is much more powerful than the other (the individual third-party sellers). Our results highlight the importance for small firms of taking value capture more seriously into consideration when they enter 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

Amazon.com, Inc. was founded on July 5, 1994. It started as an online bookstore, but quickly diversified into many other product categories, such as DVDs, CDs, video games, apparel, furniture, toys and jewelry. Today it is the largest online retailer in the United

States, with revenues of $74.45 billion in 2013. In the first quarter of 2014, Amazon's website attracted 164 million visits per month (compared to 104 million and 56 million respectively for the websites of eBay and Wal-Mart, its two largest competitors).[4] 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. With this move, Amazon became both a retailer and a platform provider. In 2013, Amazon had more than 2 million third-party sellers and they accounted for approximately 40% of Amazon's sales.[5] Amazon offers two free-shipping programs: Amazon Prime is a membership program that gives its subscribers unlimited free two-day shipping on items sold or shipped by Amazon.com for an annual membership fee of $79; while Amazon's Free Super Saver Shipping option applies to merchandise orders of at least $35 sold or shipped by Amazon, which are typically delivered within 5 to 9 business days.[6]

Several factors may increase Amazon's incentives to enter third-party sellers' product spaces. First, by selling on Amazon, third-party sellers reveal insights into how their products are performing, as Amazon has complete records of transaction data. Such market intelligence makes it easy for Amazon to 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

[4]Source: `http://tinyurl.com/k2x8jbq`, accessed November 2014.
[5]Source: `http://tinyurl.com/otydgs5`, accessed November 2014.
[6]Source: `http://tinyurl.com/k2reqtw`, accessed November 2014.

its customers and the product manufacturers.[7] Amazon may prefer selling products itself to mitigate the risks involved in the authenticity of the products, and the delivery and customer service side of the selling operation.

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. Thus, Amazon could obtain these products at lower costs than third-party sellers. Such low costs could translate either into high profits for Amazon, or low prices to consumers, which would increase their satisfaction with Amazon.

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 may have to lose this income if it chose to compete against them.[8]

Second, Amazon generates revenues from third-party sellers through a service called '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 offers. While this service provides Amazon more data for it to optimize its entry strategy, as Amazon already handles most of their logistics, its direct entry into such product spaces would not enable it to improve the quality of customer service much.

Finally, Amazon has established a reputation for sacrificing profits in favor of long-term

[7] "Amazon and J&J Clash Over Third-Party Sales," *Wall Street Journal*, November 10, 2013.
[8] Source: `http://tinyurl.com/kvqlt5z`, accessed March 2015.

growth.[9] It tries to keep prices on its core business lower than those of its competitors, and invests heavily in a diverse range of areas such as online grocery, hardware devices and cloud computing services.[10] 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 over to competing platforms such as eBay or Wal-Mart.

In sum, whether Amazon chooses to enter third-party sellers' product spaces or not, and if so, what product spaces it is more likely to enter, are empirical questions. Many platform providers today face similar trade-offs in managing their relationships with complementors (e.g., short-term profitability vs. long-term growth). Results from Amazon.com can help us to understand better the incentives that persuade platform providers' to enter their complementors' markets, or to refrain from doing so.

3 Data and Variables

We collect data from Amazon.com on four product categories— (1) Electronics & Computers, (2) Home, Garden & Tools, (3) Toys, Kids & Games, and (4) Sports & Outdoors—each of which contains a number of subcategories. In total, these four categories offer about 58 million products in June 2013. We ignore categories such as Books and Music as products in these categories are offered primarily by Amazon.

We collect data from Amazon in two rounds, first in June 2013 and then in April 2014.[11] In the first round, we seek to identify a list of products that are only offered 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

[9] See, for example, `http://tinyurl.com/palpgur`, accessed November 2014.

[10] Source: `http://tinyurl.com/k6e9z34`, accessed November 2014.

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

will choose to start selling itself, we need to collect information on as many products as possible in the first round to detect Amazon's subsequent entry. 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.

For each product that Amazon does not itself offer, we obtain the price (*Price*), shipping cost (*Shipping*), the average customer rating (*AverageRating*), and the total number of sellers offering that 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, which is typically the one that offers the product at the lowest cost (i.e., price plus shipping cost). We also check whether the seller uses Amazon's fulfillment service, and capture this information using a dummy variable, *FulfilledByAmazon*, which is 1 if a third-party product's distribution is handled by Amazon, and 0 otherwise. Although Amazon does not publish sales data about each product, it provides sales ranking for products in each product category. Past research (e.g., Chevalier and Goolsbee 2003; Sun 2012) has shown that there exists a log-linear relationship between sales ranks and actual sales, so we obtain ranking information for each product (*SalesRank*). These rankings are negatively correlated with sales: a lower ranking indicates higher sales. We exclude products that are out of stock or only sold in used condition. In total, we obtain product information for 163,853 products in 22 subcategories.

We also gather information on total number of products offered on Amazon by each third-party seller (*NumProdBySeller*) in our data set, as well as on a subset of other products these

third-party sellers offer, including their 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 that are only offered by third-party sellers in the first round, we find that Amazon has entered 4,852 (3%) of these product spaces between the two rounds. Table 1 gives the distribution of these products across different subcategories for the whole sample, and for those affected by Amazon's entry. We find that the top four subcategories—Toys & Games, Sports & Outdoors, Electronics, and Home & Kitchen—account for more than 88% of Amazon's entries, and that the percentage of products that Amazon enters in each subcategory varies from 0 to 7.34%. In five subcategories (Computers & Accessories, Video Games, Software, Grocery & Gourmet Food, and Watches), we observe no evidence of Amazon's entry.

Table 2 presents summary statistics for the product spaces that Amazon has and has not entered, based on product information collected in our first round. We take logarithms of several variables because of their skewed distributions. We first look at product prices, and find that, on average, the products Amazon chooses to offer in the second round tend to be those with higher prices. We also look at the shipping costs, and find that Amazon tends to target products where shipping costs are low. This 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 then look at these products' sales rankings and average consumer ratings. Since not all products receive consumer reviews, we compute average ratings only for products which have received at least one consumer 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 low-performing products offered by third-party sellers, we expect it to pick products with high rankings and low ratings for its entry. Our evidence supports the former explanation—Amazon is more likely to pick products with lower rankings (i.e., more popular) and higher ratings (i.e., greater customer satisfaction).

We next look at the likelihood that a third-party's product is distributed by Amazon. When a product is distributed by Amazon, the platform generates additional profits from these sellers, in addition to a percentage of sales revenue. At the same time, Amazon's customers also benefit from its customer services on these products—so the room for Amazon to improve the customer experience by its own direct entry is limited. As a result, regardless of whether Amazon's entry is motivated by profits or the desire to improve customer experience, the likelihood of Amazon entry should be lower for those products distributed via its own channels. On the other hand, Amazon might have much better information about these products, such as which suppliers they are sourced from, how much inventory space they need, etc., and this information advantage may make it easier for it to enter these product spaces, thus increasing the likelihood of its entry. The summary statistics support this latter hypothesis, suggesting that Amazon is more likely to enter the spaces of products that use its distribution system.

We also look at the number of sellers offering that product. When a large number of sellers offer same product, the intensity of competition Amazon would face if it enters is high, which is likely to reduce its incentive to do so. 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 the latter explanation appears to hold: on average, Amazon is more likely to enter spaces of products offered by many sellers, suggesting that the convenience of sourcing the products dominates the competitive effects.

Finally, we examine the total number of products that default third-party sellers offer on Amazon. On one hand, big third-party sellers can be more powerful, so Amazon may strategically want to avoid trying to squeeze them. On the other, 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.

Overall, Table 2 shows significant differences between the product spaces that Amazon chooses to enter and not to enter. The results suggest that Amazon's entry decisions are not random: Amazon is more likely to target products for entry that are popular and have great reviews.

4 Empirical Analysis

4.1 Amazon's Entry Pattern

We next model Amazon's entry decision explicitly in a regression framework. Many of the variables in Table 2 are correlated—for example, products with great 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 decisions.

Table 3 reports logit regression results where we try to identify Amazon's entry patterns. We include all products from our first round data collection that are offered only by third-party sellers. The dependent variable is a dummy, *Entered*, which is 1 if Amazon offers the product in the second round, and 0 otherwise. Model (1) includes product information such as prices, shipping costs and sales rankings, and we add the customer ratings the products received in Model (2). As not all products receive consumer reviews, instead of the average consumer ratings, we include dummy variables for different product ratings levels, with a

benchmark group consisting 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 dummies for product categories as additional controls. Finally, in Model (4), we add the logarithm of the total number of products offered by the third-party sellers.

In all four models, we find that Amazon is more likely to enter a product space when the product has a higher price, lower shipping costs and greater demand. We also find from the coefficients of the product rating dummies that, as the customer rating of the product increases, Amazon is more likely to enter. Interestingly, in contrast to the result in Table 2, we find that, after controlling for various co-variants, Amazon is less likely to enter a product space of a third-party seller that already 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 The Impact of Entry on Third-Party Products

We next evaluate the impact of Amazon's entry on third-party products. Because Amazon does not select product spaces for entry randomly, we cannot simply compare affected products to unaffected ones to evaluate the impact of Amazon's entry. We first use data from the first round to conduct propensity-score matching, which allows us to identify products that Amazon chooses not to offer during our study period as a control for similar products that it does choose to offer. We use Model (4) from Table 3 to generate propensity scores, and use them to find matches for the products affected by Amazon's entry.[12]

Next, to identify the impact of Amazon's entry, we use data from our second round to

[12] We use the single nearest-neighborhood algorithm with a caliper of 0.01 to perform the matching.

compare the characteristics of the products that Amazon has entered (the treatment group) to these matched products (the control group). 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 costs. As Amazon offers free shipping programs (via its prime and super saver deals), when Amazon offers products, their shipping costs 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 programs, we find that their shipping costs on average are significantly higher. Hence, Amazon's advantage comes primarily from its free shipping services.

We also examine the sales rankings of these products, and find that products offered by Amazon tend to be in greater demand in the second round than those in the control group—which is not surprising, as Amazon's free shipping programs 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 to increase consumer satisfaction.

Finally, we examine the likelihood that the same third-party seller continues to offer the same product in the second round. After Amazon's entry, third-party sellers are likely to face lower demand and hence are likely to stop selling the same products. On the other hand, these third-party sellers are likely to carry large stocks of these products when they are the default sellers. It may take a long time for them to reduce inventories after Amazon's entry so they may continue to offer these products. We create a dummy, *StopOffer*, which is 1 if the seller stops offering the same product in the second round, and 0 otherwise. We find that the turnover rate of product offerings by third party sellers between the first and second rounds is generally quite high—more than 40% for both affected and unaffected products.

The chance that these products are no longer offered by the same third-party sellers in the second round is 6 percentage points higher for products affected by Amazon's entry than unaffected ones.

Overall, our results suggest that Amazon's entry reduces the shipping costs for consumers for affected products, and, as a result, increases the sales of these products. At the same time, third-party sellers are discouraged from continuing to offer these products.

4.3 The Impact of Entry on Third-Party Sellers

We also examine the impact of Amazon's entry on third-party sellers by comparing shifts in the behaviors of sellers affected by Amazon's entry to those that are not so affected. We identify affected sellers from those whose products are affected, and unaffected sellers from our control group. Because our matching is conducted at the product level, it is possible that the same seller has affected products in our treatment group and unaffected products in our control group, so we drop all sellers that show up in both treatment and control groups. In the end, our data set consists of 966 affected sellers and 1,544 unaffected sellers. As some sellers may have multiple products affected by Amazon's entry, we compute, for each seller, *NumEntered*, 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).

As our propensity-score matching does not use attributes of all products offered by third-party sellers, to ensure that our results are not driven by pre-existing differences among these products, we use a 'difference-in-differences' approach, together with seller-fixed effects, to examine shifts in sellers' strategies. To that end, 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 third-party sellers offer on Amazon during the two periods. Our dependent variable is *Log(NumProdBySeller)*, the logarithm of the total number of products offered by a third-party seller in each round. For independent variables, we include *After* and its interaction with *Affected*. As we control for seller-fixed effects, the main effect of *Affected* is absorbed. Model (1) of Table 5 shows our result. We find that the interaction variable is negative and significant, suggesting that affected sellers are more likely than unaffected sellers to reduce the numbers of products they offer on Amazon. In Model (2), we replace our variable *Affected* with *Log(NumEntered)* to better capture the heterogenous impact of Amazon's entry on these sellers, and obtain similar results.

We next examine changes in sellers' behaviors at the individual product level. Using data collected on other products offered by these sellers, 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*. Although our dependent variable is a binary variable, we use linear probability models to ease the interpretation of interaction variables.[13] Our Table 3 results would seem to imply that the rational response for sellers to reduce the likelihood of Amazon's entry into their product spaces would be to start using Amazon's distribution system. On the other hand, sellers who have been adversely affected by Amazon's entry may be discouraged from working more closely with the platform. Results from Models (3) and (4) show that—consistent with this latter explanation—third-party sellers who have been affected by Amazon's entry are less likely than the control group to use its distribution system. Finally, we examine how Amazon's entry affects third-party sellers' pricing strategies. Models (5) and (6) report the results: our dependent variable is the logarithm of the product prices,

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

and the results show that there are no significant shifts in sellers' pricing strategies.

Overall, the results from Table 5 suggest that third-party sellers who have been impacted by Amazon's entry into their product spaces are discouraged from growing their businesses on the platform, and are more likely to stay away from developing close relationships subsequently.

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 likely to depend on some unobservables. For example, if a manufacturer sells its product exclusively on Amazon, the platform will not be able to enter the product space. Although the information on Amazon.com does not allow us to identify products sold directly by manufacturers, we repeat the analysis excluding all products sold by only one third-party seller, and obtain similar results (Model (1) of Table 6).

Second, large third-party sellers may have special contractual agreements with Amazon and hence may reduce Amazon's likelihood to enter. 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 (2) of Table 6).

Finally, while we include a large number of product characteristics in our logit regression, it is possible that Amazon also uses other unobservables in making its entry decisions. For example, Amazon may look at the growth in product sales instead of their current sales figures. While our conclusion that Amazon selects more promising product spaces to enter continues to hold in such cases, we take two approaches to examine robustness. First, we exclude five product subcategories—Toys & Games, Electronics, Computers & Accessories, Video Games and Software—as products in these categories are likely to exhibit significant trends. For the rest of the product subcategories, as new products are likely to have more

demand variations, we exclude all products that became available on Amazon.com after January 1, 2013. The remaining products in our data set are likely to have relatively stable demand. We repeat the logit regression with these products (Model (3) of Table 6) and find a similar entry pattern. The magnitude of several variables such as our rating variables and *FulfilledByAmazon* becomes greater.[14]

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 strongly an influence an unobservable factor must have on the selection process to nullify the causal effects identified from the propensity-matching analysis.[15] 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 to disappear in Table 4.[16] In addition, these thresholds are conservative estimates and hence any confounding unobservable would need to have an extremely high, almost deterministic, influence on selection into the treatment group and our outcome variables (DiPrete and Gangl 2004). Hence, we can argue that the effects of Amazon's entry on affected products and affected sellers are unlikely to be overturned by factors that are unobserved in our study.

[14]In addition to the logit regression, in unreported regressions, we replicate the analysis in Tables and 5 and find similar results.

[15]If we label the probability of a product being in the treatment group as p_i and the probability for the matched product being in the control group as p_j, Rosenbaum (2002) gives the bounds on the odds ratio for the two 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 on selection, he develops test statistics to show how far away Γ has to be from 1 in order for the unobservable to nullify the treatment effect.

[16]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).

5 Discussion and Conclusion

> *"Thousands of small merchants depend on Amazon.com Inc. to reach customers who otherwise wouldn't know they exist. A few of them complain, though, that Amazon sometimes eats their lunch. ... According to some small retailers, the Seattle-based giant appears to be increasingly using its Marketplace—where third-party retailers sell their wares on the Amazon.com site—as a vast laboratory to spot new products to sell, [and to] test sales of potential new goods, ..."*
>
> "Competing With Amazon on Amazon," *Wall Street Journal*, June 27, 2012.

Our research provides the first large-scale empirical study of co-opetition between platform owners and complementors, and highlights the importance for complementors of taking value capture into account when building their businesses on platforms. Because platform owners are often strategic players, complementors should not treat platform-based markets as regular markets. They need to understand platform owners' incentives and capabilities. In our setting, Amazon is both a retailer and a marketplace, and over the years has developed its capability to source products and sell them to consumers efficiently. Our results 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, our findings suggest that the appropriation risks may be higher for complementors when they work with platform owners that focus on short-term profit maximization. They also help inform complementors about the factors that do and do not influence platform owners' incentives to squeeze them. For instance, we find that the intensity of competition among complementors does not seem to affect platform owners' decisions to enter. In our setting, third-party sellers are competing with Amazon on Amazon's own web site, and under rules Amazon has designed. Checking many cases where Amazon has entered third-party sellers' product spaces, we notice that, even when third-party sellers sell their products at

lower costs (i.e., product prices plus shipping costs) to consumers than Amazon, Amazon may still present itself as the default seller. In such cases, even though Amazon adds a note on its product pages saying that the product may be offered at a lower cost by some third party sellers, many consumers may not notice this message—and even those who do may not want to spend the extra time going through the list of third-party sellers to identify such sellers. Hence, competition does not seem to concern Amazon when it comes to which products it chooses to offer. We observe similar scenarios in other settings. For example, applications supplied by platform owners (e.g., Microsoft and Apple) are often bundled with their platforms (e.g., Windows and iOS). As a result, unbundled rival complementary products thus suffer handicaps, as consumers face extra costs in searching for and installing them, so they may prefer platform owners' copycats even when their quality is inferior to the complementors' original innovations.

While our results may paint a gloomy picture of complementors' prospects, they do suggest several strategies they can use to mitigate the risk of being squeezed. First, complementors can focus on products that platform owners do not want to sell themselves. For example, as platforms tends to target popular products, complementors building their businesses around niche products targeting small market segments are less likely to face direct competition from their platforms. In our setting, Amazon's free shipping programs mean it is more likely to choose to enter product spaces where shipping costs are low—so third-party sellers offering bulky products (which involve high shipping costs) are less likely to face competition with Amazon.

Second, they can find ways to make entry difficult for platform owners. In our setting, for example, third-party sellers can try to sign exclusive contracts with manufacturers to be the sole suppliers of certain products. They may also try to hide their suppliers' information from Amazon.

Finally, complementors may choose to share more value with platform owners to reduce

their incentives to enter. As our results show, when complementors use Amazon's fulfillment services, the likelihood of its entry decreases.

Although the entry of platforms can harm complementors, our results show that such entry 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 can extend our study in multiple directions. First, our study focuses on a setting where it is difficult for complementors to deter the platform owner from entering their product spaces. In other platform markets—such as the software industry—complementors may be able to use defense mechanisms such as patents to protect their innovations. As a result, platform owners may have to acquire complementors to enter their product spaces. For example, similar to how Amazon's entry increases the popularity of affected products, Li and Agarwal (2015) find that Facebook's acquisition of Instagram expands the demand for Instagram by attracting new users who did not use any photo-sharing applications. It will be interesting to examine the generalizability of our results to settings where platform owners use different entry strategies.

Second, due to data limitations, our study does not look at how Amazon's entry strategies affect its growth. On one hand, current or potential complementors may be discouraged by Amazon's entry and switch to competing platforms. On the other hand, Amazon can attract more consumers to its platform after its entry, as its entry lowers the total cost of its offerings. A larger consumer base may thus incentivize more third-party sellers to join its marketplace. As a result, it is an open question as to how Amazon's direct competition against its complementors affects the platform's growth.

Finally, complementors should also be aware that, while direct entry into their product spaces is the most threatening and visible form of squeezing, platforms can take many other

approaches to appropriate value from their innovations (e.g., Edelman 2014). For example, eBay is purely a marketplace and has not developed the capability to operate as a retailer, so its third-party sellers do not have to worry about having to compete against the platform directly. However, eBay has raised its service fees several times to capture more value from those who sell products on its platform. In a different example, Apple often uses terms and conditions to reject applications that compete directly with its own offerings. And Facebook reduced the number of game posts from Zynga, a large third-party game publisher, on its newsfeed, which weakened Zynga.[17] Future research can explore how platform owners choose which strategies to use to squeeze complementors.

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[17]Source: `http://tinyurl.com/99oepkw`, accessed November 2014.

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Table 1: Distribution of Products Across Subcategories

Subcategory	All Products Freq.	All Products % of All Products	Affected Freq.	Affected % 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: Compare Products Affected by Amazon's Entry to Those Unaffected

	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 to Analyze 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 in parentheses. * significant at 10%; ** 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

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

Variables	(1) Log(NumProdBySeller)	(2) Log(NumProdBySeller)	(3) FulfilledByAmazon	(4) FulfilledByAmazon	(5) Log(Price)	(6) Log(Price)
After	-0.203^{***}	-0.239^{***}	0.012	0.009	-0.006	-0.008
	(0.044)	(0.042)	(0.007)	(0.007)	(0.006)	(0.005)
Affected × After	-0.285^{***}		-0.027^{***}		0.006	
	(0.077)		(0.010)		(0.008)	
Log(NumEntered) × After		-0.220^{***}		-0.023^{**}		0.010
		(0.075)		(0.009)		(0.007)
Observations	5,020	5,020	64,352	64,352	64,352	64,352
R-squared	0.034	0.032	0.001	0.001	0.000	0.000
Number of Sellers	2,510	2,510	2,036	2,036	2,036	2,036
Specifications	FE	FE	FE	FE	FE	FE

Note: Heteroskedasticity-adjusted standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Robustness Checks of Amazon's Entry Pattern

Variables	(1) Drop NumSellers = 1	(2) Drop Large Sellers	(3) Drop Products Exhibiting Trends
Log(Price)	0.237***	0.222***	0.221***
	(0.014)	(0.018)	(0.019)
Log(Shipping)	−0.110***	−0.146***	−0.116***
	(0.021)	(0.026)	(0.025)
Log(SalesRank)	−0.130***	−0.149***	−0.211***
	(0.009)	(0.011)	(0.014)
$1 \leq$ AverageRating < 2	−0.152	−0.257	−0.170
	(0.155)	(0.210)	(0.266)
$2 \leq$ AverageRating < 3	0.008	0.103	0.204
	(0.097)	(0.116)	(0.148)
$3 \leq$ AverageRating < 4	0.157***	0.145**	0.480***
	(0.055)	(0.069)	(0.080)
$4 \leq$ AverageRating ≤ 5	0.192***	0.265***	0.564***
	(0.040)	(0.051)	(0.060)
FulfilledByAmazon	−0.097**	−0.214***	−0.249***
	(0.041)	(0.051)	(0.059)
Log(NumSellers)	0.292***	0.323***	0.411***
	(0.018)	(0.020)	(0.025)
Log(NumProdBySeller)	0.116***	0.068***	0.109***
	(0.008)	(0.015)	(0.011)
Dummies for Categories	Yes	Yes	Yes
Observations	119,894	111,755	76,693
Pseudo R-squared	0.04	0.04	0.07

Note: Heteroskedasticity-adjusted standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.