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Abstract

There is an active policy debate seeking to understand whether Amazon first-party entry in competition with third-party merchants harms these merchants, and ultimately consumers, on Amazon Marketplace. Some argue that the exploitation of third-party data permits seller expropriation and reduces innovation while others claim that such entry permits the internalization of important externalities, benefiting consumers and merchants alike. We seek to inform this debate by measuring the predictors and effects of Amazon first-party retail entry on consumer and third-party merchant outcomes in the Home & Kitchen department of Germany's Marketplace between 2016 and 2021. We find Amazon entry both within and across products is associated with modest positive effects on both consumer and third-party merchant outcomes more consistent with mild market expansion than with appropriating third-party sales. We find that both Amazon and large third-party merchants' entry is associated with fewer subsequent new product introductions, but that these are consistent with regression to the mean rather than causal effects on innovation. Finally, we find that the predictors of Amazon's within-product entry decisions are more consistent with a strategy that makes Marketplace more attractive to consumers than of third-party seller expropriation, including consideration of predictors based on aggregated Marketplace data. While the empirical setting presented challenges for estimating causal effects, our results are broadly inconsistent with systematic adverse effects of Amazon entry on Amazon Marketplace.

Keywords: Amazon, Marketplace, Digital Platforms, Hybrid Platforms, Entry, Expropriation

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Amazon Entry on Amazon Marketplace*

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August 18, 2022

Abstract

There is an active policy debate seeking to understand whether Amazon first-party entry in competition with third-party merchants harms these merchants, and ultimately consumers, on Amazon Marketplace. Some argue that the exploitation of third-party data permits seller expropriation and reduces innovation while others claim that such entry permits the internalization of important externalities, benefiting consumers and merchants alike. We seek to inform this debate by measuring the predictors and effects of Amazon first-party retail entry on consumer and third-party merchant outcomes in the Home & Kitchen department of Germany's Marketplace between 2016 and 2021. We find Amazon entry both within and across products is associated with modest positive effects on both consumer and third-party merchant outcomes more consistent with mild market expansion than with appropriating third-party sales. We find that both Amazon and large third-party merchants' entry is associated with fewer subsequent new product introductions, but that these are consistent with regression to the mean rather than causal effects on innovation. Finally, we find that the predictors of Amazon's within-product entry decisions are more consistent with a strategy that makes Marketplace more attractive to consumers than of third-party seller expropriation, including consideration of predictors based on aggregated Marketplace data. While the empirical setting presented challenges for estimating causal effects, our results are broadly inconsistent with systematic adverse effects of Amazon entry on Amazon Marketplace.

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1 Introduction

Amazon.com is the world's largest online retailer and one of the most valuable companies in the world. With size comes scrutiny, and the company has been criticized by regulators and policymakers worldwide for a number of its business practices, including those related to its operation of Amazon Marketplace, its e-commerce platform/online marketplace that permits third-party merchants to sell to consumers in competition with Amazon's first-party retail business. In November 2020, the European Commission (EC) sent a Statement of Objections to Amazon regarding its use of "non-public marketplace seller data ... to avoid the normal risks of retail competition and leverage its dominance in the market for the provision of marketplace services in France and Germany" (European Commission 2020). In the US, the October 2020 House of Representatives' Antitrust Subcommittee report on its investigation into competition in digital markets spent 82 pages on Amazon, concluding "Amazon's dual role as an operator of its marketplace that hosts third-party sellers, and a seller in that same marketplace, creates an inherent conflict of interest. This conflict incentivizes Amazon to exploit its access to competing sellers' data and information, among other anticompetitive conduct" (House Judiciary Committee's Antitrust Subcommittee 2020). These concerns have also garnered significant popular media coverage, with multiple high-profile and widely-read investigative reports in leading US media outlets (Weise 2019, Mattioli 2020a, Mattioli 2020b), and they extend beyond Amazon, with considerable interest about vertically integrated ("hybrid") online marketplaces from policymakers worldwide.[1]

As a consequence of this policy interest, there is a large and growing literature in both law and economics seeking to understand the consequences to consumers and third-party merchants of hybrid marketplaces' business practices. Khan (2019), analyzing Amazon Marketplace, argues, *inter alia*, that its dual role creates a fundamental conflict of interest that enables it to privilege its retail operations (e.g. via its search algorithm) and appropriate business information of third-party merchants to inform its product entry decisions for both retail and Private Label products.[2] The focus of this paper is on Amazon's entry decisions, and here the economics literature is more mixed. Etro (2021b) shows that, because Amazon can monetize third-party sales via commissions, it has no reason to foreclose third-party rivals, and instead has an incentive to enter only when it has a competitive advantage from doing so (e.g. when it can exploit its efficient logistics operations) or when there is third-party-merchant market power (e.g. via Private Label entry).[3]

[1]For example the European Commission's incipient regulations for digital markets, the Digital Markets Act, forbids "gatekeeper platforms" from using data generated by business users of its "core platform services" in competition with those users. While the definition of gatekeeper platforms is still being finalized, it is clearly meant to include firms beyond Amazon (Caffarra and Morton 2021) and the determination of what integrated online marketplace owners may and may not do with respect to data on their platforms is likely to remain a first-order competition policy question for the foreseeable future.

[2]See also House Judiciary Committee's Antitrust Subcommittee (2020).

[3]Similarly, Nosko and Tadelis (2015), analyzing eBay, show that decentralized sellers do not internalize the impact of their

Hagiu, Teh and Wright (2020) also mention the benefits of marketplace retail entry on third-party market power, but suggest there may be inefficiencies if the marketplace self-preferences or imitates successful third-party products using information on those products' demand or sales, a point also analyzed in Madsen and Vellodi (2021).[4] In essence, there are papers analyzing the effects of Amazon's (assumed) use of third-party merchants' data to enter with imitation products, Amazon entry to internalize Marketplace externalities to the benefit of consumers, or possibly both.

In this paper, we seek to assess the empirical relevance of these arguments by using proprietary data from 2016-2021 from Amazon.com to measure the predictors and effects of first-party Amazon entry on Germany's Amazon Marketplace.[5] We first characterize patterns of entry across the major "departments" on Amazon's Germany Marketplace, before settling on the computationally manageable task of analyzing detailed entry patterns in the entirety of the Home & Kitchen department.[6]

We have four sets of results. First, we characterize the types of Amazon entry. We find that Amazon in present in products that earn 39.0% of overall Home & Kitchen revenue in our sample period, and introduced or entered products that earn 29.5% of total Home & Kitchen revenue. Almost half of the revenue from products in which Amazon is present (48.7%) comes from products where there was *de novo* Amazon entry, that is products Amazon introduced that no third-party merchant previously offered on Marketplace. Private Label products earn a tiny fraction of this total (0.3% of total Home & Kitchen revenue).

Second, we estimate the effects of Amazon entry into pre-existing products introduced to Marketplace by a single third-party merchant (accounting for 20.3% of Home & Kitchen revenue from products in which Amazon is present). Excluding entry into products early in their lifespan (because such entry is likely correlated with unobserved demand shocks), we find that Amazon entry into pre-existing products is associated with slightly lower third-party merchant prices, lower third-party product availability (a measure of product quality), with no estimated effect on total third-party revenue, quantity, or number of active merchants in the 40 weeks post-entry. By the same token, Amazon itself exits frequently (a 40% exit rate in the 40

negative actions on the marketplace as a whole, inducing a reputational externality across sellers. The marketplace can mitigate this by promoting high-quality sellers in its search results; a hybrid marketplace may also want to do this, or to enter as a first-party retailer in those markets populated with low-quality sellers.

[4]Other earlier papers related to our work include Hagiu (2009), Hagiu and Wright (2015), and Anderson and Bedre-Defolie (2019). A range of recent papers also analyze a hybrid marketplace's choice of commissions, identifying both an incentive to raise third-party commissions to shift demand to its own products and an incentive to reduce commissions to attract third-party merchants to the platform, lower their prices, and increase the marketplace's overall value. Different modeling frameworks and assumptions influence the strength of each effect, with consequent differences in policy recommendations (Anderson and Bedre-Defolie 2021, Etro 2021a, Zennyo 2021). As the focus of this paper is on Amazon's entry decisions, we do not speak to the conclusions of these papers.

[5]This paper focuses exclusively on entry on Amazon Marketplace, and does not speak to policy concerns regarding other aspects of Amazon's Marketplace business practices or Amazon's non-Marketplace business practices.

[6]For expositional convenience, in everything that follows we refer to Amazon.com's Germany Marketplace simply as "Marketplace." Similarly, it should also be understood throughout the paper that our results only analyze data in the German Marketplace's Home & Kitchen department. We speak to the external validity of our policy conclusions in light of these limitations in Section 5.

weeks post-entry), sometimes charges slightly lower prices than pre-entry third-party averages, and (again excluding entry into newly-born products) earns sales typically 3-7% of third-party pre-entry totals.

The economics literature typically classifies the effects of entry into three categories: "cannibalization," when a firm's entry with a new product earns revenue at the expense of its own pre-existing products, "business stealing," when a firm's entry with a new product earns revenue at the expense of rival firms' products, and "market expansion," when a new product earns revenue not previously being earned by any pre-existing products (e.g. by satisfying consumer demand not previously being satisfied by pre-existing products).[7] Taken together, the results summarized in the previous paragraph are consistent with Amazon entry within existing products causing (on net) mild market expansion. We also look at the effects of Amazon and large third-party merchants' ("Big 3P") entry into pre-existing products on smaller merchants' subsequent innovation activity, measured by their willingness to introduce new products. We find that both Amazon and Big 3P entry is correlated with reductions in the introduction of new products in the Home & Kitchen department by merchants that have previously introduced successful products in this department. The relationship between Amazon's entry and new product introductions are smaller in absolute value than those of large third-party entrants and both likely capture "regression to the mean" in new product introductions rather than the causal effects of either Amazon or Big 3P entry (i.e. that merchants that previously introduced innovative products are not guaranteed to again be able to do so).

Third, we expand our analysis beyond entry into pre-existing products to examine the cross-product effects of Amazon entry, including Amazon Private Label ("PL") entry. Cross-product entry is important from a policy perspective given the magnitude of *de novo* Amazon entry on Marketplace; such entry will harm third-party merchants only to the extent it draws demand from third-party products. When analyzing the effects Amazon, Big 3P, and smaller third-party entry with new products within Home & Kitchen subcategories (e.g. Robotic Vacuum Cleaners), we find that over an 80-week period Amazon entry is associated with mild market expansion, with no evidence of business stealing. To measure the effects of the subset of new Amazon products that is Private Label entry, we rely on Amazon search results to define both a set of substitute products as well as a set of control products and find results qualitatively similar to that for within-product entry: excluding effects on substitutes for which there are differences in pre-entry trends in outcomes, Amazon PL entry is associated with an increase in total quantities sold of third-party substitute products, with no estimated change in average third-party prices or total third-party revenue. Furthermore, Amazon's PL price is lower for some entry cohorts and has PL sales at a level 1-10% of pre-entry third-party

[7] See Mankiw and Whinston (1985), noting that they call the market expansion effect the "product diversity" effect, or Davis (2006) for an application of these ideas in the motion picture industry. All effects are likely to be present when a new product enters a market, in which case the goal is often to measure which effects are stronger, those related to business stealing (and possibly cannibalization) or those related to market expansion.

totals.

Fourth, we consider what factors predict Amazon entry within pre-existing Home & Kitchen products, accounting both for covariates that are likely to be observable to both Amazon and third-party merchants, as well as those observable only to Amazon based on aggregated (across merchants) Marketplace data.[8] Taking Amazon entry decisions in isolation, we find that, Amazon tends to enter high-growth, low-competition products. Comparing Amazon entry decisions to those of the largest third-party merchants, however, shows that Amazon tends to enter low-growth, (even-lower-)competition, and low-availability (i.e. low-quality) products. These effects are more consistent with a strategy that seeks to make Marketplace more attractive to consumers (via expanding variety, lessening third-party market power, and/or enhancing product availability) than one that seeks to expropriate third-party merchant sales. Furthermore, those predictors that are based on aggregated Marketplace data (measures of demand/demand growth, competitiveness, and availability) are more consistent with Amazon entering products that make Marketplace more attractive to consumers than to misappropriate third-party sellers.

What are the policy implications of our results "in the round"? Where we have the greatest confidence that our results on the *effects* of Amazon entry are causal, there is evidence that such entry causes mild market expansion: our cross-product analysis shows that Amazon's (substantial) *de novo* entry in the Home & Kitchen department appears to increase subcategory revenue and our within-product analysis shows small incremental revenue and quantity effects without displacing third-party sales. Similarly, our results on the *predictors* of Amazon entry suggests Amazon's entry strategy in the Germany Home & Kitchen department is more consistent with making Marketplace more attractive to consumers than expropriating third-party merchants, including consideration of predictors based on aggregated Marketplace data. While the empirical setting presented challenges for estimating causal effects, our results are broadly inconsistent with systematic adverse effects of Amazon entry on Amazon Marketplace.

We obtain these results as follows. We begin our analysis by describing some basic facts about Marketplace outcomes in our sample: across the 25 product "departments" covering 85% of total Marketplace revenue that we study, we show that revenue and variety are steadily increasing and that third-party sales are an increasing share of this revenue. Entry is a core element of competitive Marketplace dynamics across departments: in our sample, the average end-of-sample revenue share of all products that entered during our sample period is over 90%, with little variability across departments. As the general patterns are similar

[8] Our empirical analysis of the factors that predict Amazon entry is conducted at the product level and therefore aggregates information across third-party merchants in line with Amazon's Seller Data Protection Policy. Section 4.1 describes this policy (and its received criticism) and Section 4.2.2 describes in detail how our empirical analysis can potentially reveal the differential impact of factors observable to Amazon but not third-party merchants, but not factors that are based on seller-specific versus aggregated data.

across different product departments and the computational burden of analyzing the entirety of Amazon's Marketplace is considerable, we focus the remainder of our analysis on a single Marketplace department: Home & Kitchen Items. Given the patterns summarized above, we think it likely that most Marketplace departments would be representative of overall Marketplace entry patterns; we selected Home & Kitchen as it high in overall size (8th-largest in net revenues) and in the share of first-party sales (also 8th-largest), providing a rich environment to measure the predictors and effects of Amazon entry.

The core of our dataset is a record of every sale of an item in the Home & Kitchen department on the Germany Marketplace from July 12, 2016 to May 31, 2021. This data includes the product sold, what Amazon calls an ASIN, the merchant who sold it, the date and time of sale, and the price paid inclusive of tax and shipping and/or any other charges. The data also indicate whether a product is an Amazon Private Label product (e.g. "Amazon Basics"), in which case Amazon is the only seller. We also have information on end-of-day offers at the product-day level, but use this sparingly as it is several orders of magnitude larger than the sales data, imposing a significant computational burden, even in a single product department.

We distinguish two types of within-sample new product entry on Marketplace: "multi-merchant" new products, those that see two or more merchants making sales in the first four weeks of the product's existence on Marketplace and "single-merchant" new products, those for which there is only one seller making sales in the first four weeks of the product's existence on Marketplace. The policy debate, and therefore our analysis, focuses largely on the predictors and consequences of two types of entry: (1) entry by Amazon into single-merchant products first offered by third-party merchants and (2) new product entry of Amazon Private Label products in competition with other pre-existing products.

We first measure the effects of Amazon entry on consumer and merchant outcomes, both to determine if the anecdotes cited in the popular press are indicative of widespread Marketplace patterns and to benchmark potentially negative effects of entry on third-party merchants against potentially positive effects on consumer outcomes like prices and quality. To do so, we rely on a staggered difference-in-difference research design, a topic of considerable recent research in the econometrics literature (Roth, Sant'Anna, Bilinski and Poe 2022, Wooldridge 2021). We focus our effects analysis first on measuring the causal effects of Amazon entry *within* products in competition with pre-existing third-party merchants. Because we observe the exact timing of Amazon entry and focus our measurement on the weeks immediately before (20) and after (40) this entry, we can hope to pin down the causal effects of Amazon entry on product-level prices and quality (measured by availability), as well as third-party merchant revenue, quantity, and number of active merchants (net entry and exit). We also examine the impact of Amazon within-product entry on affected merchants subsequent new product introductions, with results of all of these analyses summarized in the paragraphs above.

We then extend our effects analysis to examine cross-product effects of Amazon entry. To do so requires defining a set of substitute products. For our general approach, we exploit Amazon's definition of "subcategories" (of which there are over 1,600 in the Home & Kitchen department) and analyze cross-product effects within each subcategory. For Amazon Private Label products (of which there are approximately 150 in the Home & Kitchen department), our process to define substitutes began with asking Amazon to examine all searches in which each Private Label showed up in the first page of results (=20 products), and share with us all the other products that also showed up in those searches. We included as substitute products for each Private Label product the five largest revenue products from this first page of results that were in the same Home & Kitchen subcategory. We also defined a control group for each set of such "treated" products as all those products in the subcategory that never were on the first page of search results that included that Private Label product. Such products' absence in the search page results supports the assumption that they are not substitutes for the Amazon private label product, but their presence in the same subcategory supports the assumption that they may pick up similar unobservable demand, cost, or competition shocks.

We close our empirical analysis by estimating some of the factors that predict Amazon's entry into specific Home & Kitchen products and benchmark these against the entry decisions of large third-party (3P) merchants. As ever, firms like to enter markets with high and/or growing demand, low and/or falling costs, and low competition. The recent literature on hybrid marketplaces, summarized above, highlights the tradeoffs hybrid marketplaces may face in their entry decisions. Hybrid marketplaces seeking to maximize the long-run value of the marketplace will make entry decisions that seek to internalize externalities that are unlikely to be internalized by independent third-party merchants, including enhancing variety, reducing seller market power in individual products, and maximizing availability (Cabral and Xu 2021). Alternatively, hybrid marketplaces may exploit their dual position as retailer and marketplace provider by using marketplace data to identify successful products, expropriating the value of third-party sellers and harming future innovation on the platform (Hagiu et al. 2020, Madsen and Vellodi 2021). In our analysis, we seek to distinguish between these theories, taking care to assess the impact of predictors that are likely to be observable to third-party merchants versus those that are likely to be observable only to Amazon by virtue of its ownership of Marketplace data. A final section concludes by placing our empirical results in the policy context we seek to address.

This paper is related to several literatures in law, marketing, and economics. First, there is the substantial and growing literature, summarized above, analyzing online marketplaces, including the choice to be a marketplace or reseller or both ("hybrid") and the consequences for consumer and third-party merchant outcomes under each alternative (with Amazon the explicit or implicit subject of inquiry). We seek to test the predictions of these theories with respect to Amazon's entry decisions.[9]

We also contribute to the literature seeking to measure the competitive effects of entry. Recent papers have focused on how endogenous product positioning and market structure via entry and exit can influence topics such as measures of market competitiveness, product variety, and the evaluation of merger effects (Eizenberg 2014, Arcidiacono, Bayer, Blevins and Ellickson 2016, Wollmann 2018, Ciliberto, Murry and Tamer 2021). The majority of this literature uses structural econometric methods to infer competitive effects, often in the absence of price and/or quantity information (Berry and Reiss 2007). We differ from this literature by substituting data for structure: we can measure well prices, quantities, and (some) quality attributes for the full set of competitors in a rich competitive environment.

Our analysis is a natural extension of the literature in marketing and economics analyzing the competitive effects of Walmart's entry into general merchandise and grocery markets. Indeed the issues raised in the debate about Amazon's business practices echo those raised in the 1990s and 2000s about Walmart, including the consequences of Walmart's success on small businesses, entrepreneurship, and innovation. This literature finds large and significant negative effects of Walmart and other "big-box" retail stores on small general merchandise retailers' survival (Jia 2008, Haltiwanger, Jarmin and Krizan 2010), but the opposite effects of Walmart's ("Superstore") entry into grocery markets, with little or no effect of Walmart entry on prices (Basker and Noel 2009, Arcidiacono, Ellickson, Mela and Singleton 2020), a positive impact on product availability (Matsa 2011), and survival effects concentrated on large and not small competitors (Ellickson and Grieco 2013, Arcidiacono et al. 2016).

Our work is closest to three other papers in the small but growing empirical literature looking specifically at Amazon Marketplace outcomes. Gutierrez (2021) estimates a structural econometric model of Amazon Marketplace, estimating consumer demand for products, allowing third-party sellers and Amazon to set product prices and platform fees, and simulating counterfactual regulations such as requiring Amazon to be only a reseller or only a marketplace. We differ from this work by measuring the predictors and effects of Amazon first-party and Private Label entry on consumer and third-party outcomes, including longer-run product entry decisions. Zhu and Liu (2018) looks also at the predictors of Amazon's entry decisions, but on a small subset of (US) Marketplace products from two months in 2013 and 2014. Our dramatically richer (and more recent) data enables us to more credibly measure the effects and predictors of Amazon entry and addresses concerns about the external validity of their results. Finally, Cabral and Xu (2021) analyze price gouging by third-party merchants early in the COVID-19 pandemic, finding they charged

[9] There is a related policy debate and academic literature concerned with self-preferencing on online marketplaces and its consequences for consumer outcomes, e.g. European Commission (2020), Hagiu and Spulber (2013), and Lee and Musolff (2021). While relevant for the outcomes we see, we do not have the data to investigate this topic.

prices for 3M masks 240% higher than Amazon's 2019 price and that, when Amazon was stocked out, new (entrant) sellers charged prices much higher than pre-existing sellers, arguing that existing sellers' concerns for their reputations limited their desire to charge more than they did. One of the threads of our empirical analysis is to explore whether Amazon's entry decisions are consistent with similar reputational concerns for Marketplace as a whole.

The rest of this paper proceeds as follows. Section 2 reports aggregate trends on Germany's Marketplace and motivates our decision to study the Home & Kitchen department. Section 3 reports our analysis of the effects of Amazon entry, both within pre-existing Marketplace products as well as across products. Section 4 analyzes what factors predict Amazon entry within pre-existing products, both in the aggregate and relative to big third-party merchant competitors. Section 5 concludes by summarizing the implications of our results for the policy debate regarding entry on Amazon marketplace.

2 Germany Marketplace Facts

2.1 Aggregate Marketplace Trends

To measure the impact of Amazon entry on Amazon Marketplace, we obtained detailed data from Amazon.com about their Germany Marketplace from July 12, 2016 to May 31, 2021. Our decision to focus on Germany was due to its policy relevance: it is the largest of the countries that is the focus of the EC investigation into some of the same questions that we are investigating (European Commission 2020). That being said, we have no reason to expect the patterns that we find in Germany would differ meaningfully for any of Amazon's other individual country marketplaces worldwide.[10]

In principle, we had access to information about every offer and sale of every item on the Germany Marketplace during our sample period. In practice, this was too much information to analyze in a concise manner. We therefore began by describing aggregate trends for the whole of the data before doing a more detailed analysis on a representative subset of the full Marketplace data.

Figure 1 displays the total revenue and revenue share by merchant type on the whole of Germany's Marketplace in our 5-year sample period.[11] Amazon sales are distinguished between first-party sales (where other merchants could also be offering the product) and Private Label sales (where they cannot). As can be seen there, Marketplace revenue is growing in the aggregate, as is the share of revenue coming from third-party

[10] Amazon currently operates Marketplace in 19 countries: 3 in North America, 8 in Europe, and the remaining 8 spread over Asia, the Middle East, Brazil, and Australia.

[11] For reasons of confidentiality, we will sometimes, as here, omit information from figures and tables that Amazon considers sensitive competitive information.

sellers. Amazon Private Label revenues are tiny as a share of total Marketplace activity (0.3% of overall sales), and are thus barely visible in the figure.

Table 1 reports summary statistics for some key variables across 25 of the largest Marketplace departments covering approximately 80% of its revenue in our sample period. Amazon's Germany Marketplace has annual revenue in our sample period of 160.0b Euros on sales of over 21.5 million distinct products. Amazon's share of sales within departments is fairly constant, with departments with particularly high values (Books, Home Entertainment, PC, Camera, and Major Appliances) all offering a significant share of high-value (often branded) products offered by a relatively small number of major manufacturers for which Amazon's efficient supply chain and logistics operations likely provide it with a competitive advantage relative to third-party sellers.[12] Entry is an important phenomenon across all categories: the average share of revenue sold to products that entered during our sample period is 90.7% and is uniformly high, with a low value of 79.5% for Office Products.

With individual sales numbering in the billions and offers an order of magnitude larger than that, in what follows we focus our detailed analysis on a subset of this data. As patterns of entry are relatively homogeneous across departments and understanding the dynamics of competition is not possible using random subsamples, in the rest of our analysis we focus on characterizing the predictors and consequences of Amazon entry in the entirety of a single Department: Home & Kitchen items. Given the patterns summarized above, we think it likely that most Marketplace departments would be representative of overall Marketplace entry patterns; we selected Home & Kitchen as it high in overall size (8th-largest in net revenues) and in the share of first-party sales (also 8th-largest), providing a rich environment to measure the predictors and effects of Amazon entry. Among high-revenue categories, it also had relatively few products, reducing the computational burden of the analysis. In the next subsection, we describe in greater detail the data we use in our analysis of the Home & Kitchen department.

2.2 Marketplace Data in the Home & Kitchen department

To address the predictors and effects of Amazon entry in the Home & Kitchen department on Amazon's Germany Marketplace, we obtained detailed sales and offer data from Amazon covering the period July 12, 2016 to May 31, 2021. This data includes the product sold, what Amazon calls an ASIN, the merchant who sold it, the date and time of sale, and the price paid inclusive of tax and shipping and/or any other charges[13]. The data also indicate whether a product is an Amazon Private Label product (e.g. "Amazon Basics"),

[12]For reasons of confidentiality, Table 1 does not report the share of Amazon sales in each category.

[13]ASIN = Amazon Standard Identification Number. These are broadly analogous to a UPC code in a supermarket scanner dataset.

in which case Amazon is the only seller. We also have information on end-of-day offers at the product-day level, but use this sparingly as it is several orders of magnitude larger than the sales data, imposing a significant computational burden, even in a single product department.

Figures 2-4 show aggregate trends in some of the variables that play an important role in our analysis. Figure 2 is the Home & Kitchen-specific version of Figure 1 and shows similar patterns of revenue growth overall and by merchant type as Marketplace as a whole, albeit with (as intended) a higher share of first-party (Amazon retail) sales. Figure 3 reports the total number of products in the Home & Kitchen department making 1,000 Euros/month in sales, a measure of variety, and shows it growing steadily over our sample period. Figure 4 reports the average availability of products in the Home & Kitchen department by Amazon/third-party merchants, showing both are quite high before onset of the COVID-19 pandemic in March 2020.[14]

Our key object of interest is entry. We distinguish between new product entry and the (simple) entry of a merchant (Amazon or third-party) into an existing product. We define both types of entry as the date of first sale of that new product/merchant in an existing product.

Within new-product entry, we differentiate between "multi-merchant" new products, those that see two or more merchants making sales in the first four weeks of the product's existence on Marketplace, and "single-merchant" new products, those for which there is only one seller making sales in the first four weeks of the product's existence on Marketplace. The remaining products, those that are present at the beginning of our data, we call "incumbent products." Figure 5 shows that entry of single-merchant new products is far more common and Figure 6 shows that, conditional on multi-merchant entry, there are sometimes many merchants entering within products' first four weeks of life. The policy debate, and therefore our analysis, focuses largely on the predictors and consequences of two types of entry: (1) entry by Amazon into single-merchant new products introduced to Marketplace by third-party merchants and (2) new product entry of Amazon Private Label products in competition with other pre-existing (third-party) products. In the balance of the paper, we seek to measure the effects, predictors, and other evidence related to these two types of entry.

3 Amazon Entry on Amazon Marketplace: Effects

We first measure the effects of Amazon entry on consumer and merchant outcomes, both to determine if the concerns raised about Amazon's entry decisions in ongoing EC and US investigations are reflected in their actual entry patterns in a large amount of Marketplace data and to benchmark potentially negative effects

[14]We explored whether any of the qualitative results of our analysis were sensitive to the inclusion of data from the pandemic period and found that they were not.

of entry on third-party merchants against potentially positive effects on consumer outcomes like prices and quality.

For example, (Khan 2016) provides examples from the popular press of Amazon exploiting Marketplace data in its own entry decisions, concluding "In using its Marketplace [data] this way, Amazon increases sales while shedding risk. It is third-party sellers who bear the initial costs and uncertainties when introducing new products; by merely spotting them, Amazon gets to sell products only once their success has been tested." House Judiciary Committee's Antitrust Subcommittee (2020) provides more detail: in the opening remarks to the section covering Amazon titled "Appropriation of Third-Party Seller Data," it reports that "... the Subcommittee heard repeated concerns that Amazon leverages its access to third-party sellers' data to identify and replicate popular and profitable products from among the hundreds of millions of listings on its marketplace. Armed with this information, it appears that Amazon would (1) copy the product to create a competing private-label product; or (2) identify and source the product directly from the manufacturer to free ride off the seller's efforts, and then cut that seller out of the equation."

In this section of the paper, we characterize the types of Amazon entry in our data (in subsection 3.1) and seek to measure the effects of Amazon entry, both into existing Marketplace products (in subsection 3.2) as well as in competition with other distinct products (including Private Label entry; in subsection 3.4). In Section 4, we address the predictors of Amazon's entry decisions, including whether they appear to exploit access to aggregate data on third-party merchants.

3.1 Types of Amazon entry

Before we begin our analysis of the effects of Amazon entry, it is important to situate our analyses in the broader scope of Amazon's Marketplace presence. Our estimation sample is selected to speak to the policy issues described above. Table 2 describes Amazon's presence across product types in the Home & Kitchen Department on Germany's Marketplace, and the share of revenue from those products in which it entered in our sample period, broken out by the type of product it entered (incumbent, single-merchant, or multi-merchant).[15]

Within the Home & Kitchen department on Germany's Marketplace, we find that Amazon in present in products that earn 39.0% of overall Home & Kitchen revenue in our sample period, and introduced or entered products that earn 29.5% of total Home & Kitchen revenue.[16] Almost half of the revenue from products in which Amazon is present (48.7%) comes from products where there was *de novo* Amazon entry,

[15] See the subsection above for definitions of each of these types of products.

[16] Across all products in which Amazon is ever active, Amazon itself earns 77% of the products' total revenue.

that is products Amazon introduced that no third-party merchant previously offered on Marketplace. Private Label products earn a tiny fraction of this total (0.3% of total Home & Kitchen revenue). We explore the consequences of this type of entry when we estimate cross-product effects in Section 3.4 below.

A further 20.3% of Home & Kitchen revenue from products in which Amazon is present comes from products first sold by a single third-party merchant where Amazon entry occurred no earlier than the fifth week of the product's life (see the next paragraph for why we focus on such entry). The effects of this entry is the focus of the analysis of the next subsection.

3.2 Effects of Amazon entry into existing products

3.2.1 Empirical framework

Given its size and scope, our data provide a wealth of entry events to try to measure the causal effects of Amazon entry into products first introduced to Marketplace by third-party merchants. This focus reflects two conditions: (1) that a product was first introduced to Marketplace by a third-party merchant and (2) that Amazon later entered in competition with it. In our analysis to come, we strengthen somewhat the first condition in a way consistent with the policy concerns by focusing on products exhibiting *single-merchant entry* by a third-party seller, defined as there having been a single (here, third-party) merchant selling the product in the first four weeks of its "lifespan" on Marketplace. We feel that imposing a four-week window on the entry events we study excludes two types of entry that are not the focus of the policy debate: (1) Amazon entry into products newly offered by manufacturers for which there are multiple firms entering (including Amazon), but that a third-party merchant happened to be first to make a sale, and (2) Amazon entry into single-merchant new products before Amazon would have had time to infer such products' potential value.

Because we observe the exact timing of Amazon entry and focus our measurement on its effects immediately before and after entry, we can hope to pin down the causal effects of this entry on a host of consumer and merchant outcomes using a "staggered differences-in-differences" research design. For each product, we define its week of birth as the week of its first sale and measure the impact of Amazon entry at some later week relative to products that never witness Amazon entry or do so at an even later entry week. While there is precedence for such an approach in the literature analyzing Walmart entry (Arcidiacono et al. 2020), such research designs involving multiple periods and variation in treatment timing ("staggered treatments") have received considerable attention in the recent econometrics literature, finding that when there is heterogeneity in treatment effects across treatment cohorts (measured for us in product age) and/or time, imposing common treatment effects can cause "forbidden" comparisons between products that have both been treated, with adverse consequences on the estimated treatment effect(s).[17] We address this concern by first estimating flexible specifications that avoid such comparisons before imposing common treatment effects that can be supported by the data (enhancing precision).

In what follows we present a range of results based on a common econometric specification. Letting $i = 1, \ldots, N$ index products, $m = 1, \ldots, M$ index merchant types (with details depending on the specification), $t = 1, \ldots, T$ index individual weeks in our sample period, $a = 1, \ldots, A$ index a product's age in weeks, $AmEntry_i$ index the product age at which Amazon entered product i, and W index the number of post-treatment weeks over which we measure effects ($W = 40$ in most of our results), the regression equation for analyzing product-level outcomes like prices, quantities, or revenues is:

$$y_{imt} = \eta + \gamma_i + \gamma_m + \gamma_a + \gamma_t + \sum_{r=5}^{A} \sum_{s=0}^{W} \tau_{rs,m} * d_{i,AmEntry_i=r} * d_{a=r+s} + \epsilon_{imt} \tag{1}$$

where y_{imt} is an outcome of interest (e.g., price, quantity, availability) of product i received/shipped/earned by merchant type m in week t, γ_i, γ_m, γ_a, and γ_t are product or merchant (depending on specification), age, and time (week) fixed effects, $\tau_{rs,m}$ is the estimated treatment effect of Amazon entry for cohort r in week s after Amazon entry, with separate effects estimated by merchant type m, $d_{i,AmEntry_i=r}$ is a dummy equal to 1 if product i saw Amazon entry at age r (which happens at the earliest at age $a = 5$ in our data), and $d_{a=r+s}$is an age dummy equal to 1 in the s^{th} week after Amazon's entry for product i (given for each i by r), where $s = 0, \ldots, W$. This specification estimates flexible treatment effects for each separate cohort of product ages at which Amazon enters, $r = 5, \ldots, A$, for each week after Amazon enters a product, $s = 0, \ldots, W$ (with $s = 0$ corresponding to effects in the week of entry). This specification is analogous to that commonly estimated in the staggered treatment effects literature for cohorts that are aligned on a product's age rather than calendar time (and limited in effect to a total of W weeks).[18] We highlight that this specification estimates separate parameters measuring the effect of Amazon entry on third-party merchants, $\hat{\tau}_{s,3P}$, as well as an "effect" of Amazon entry on Amazon's own outcomes, $\hat{\tau}_{s,Am}$. The latter can be interpreted as measuring the level of the Amazon outcome (by cohort and week of Amazon entry) relative to pre-entry average or total (depending on specification) third-party outcomes. For expositional convenience and to foster comparability with the impact of Amazon on third-party outcomes, we call these

[17] See Roth et al. (2022) for an accessible survey and Sun and Abraham (2021), Goodman-Bacon (2021), Callaway and Sant'Anna (2021), and Wooldridge (2021) for further details. Goodman-Bacon (2021) provides helpful intuition about how forbidden comparisons can arise and Wooldridge (2021) presents the problem and solutions in a framework readily accessible to applied researchers. Our results were produced with an R package helpfully provided by Sun and Abraham (2021).

[18] Thus τ_{50} is the effect of contemporaneous entry of the first cohort (those that saw entry at age $a = 5$), τ_{51} is the effect in the first week post-entry of this first cohort, etc. (for 40 total weeks), and τ_{60}, τ_{61}, ... measure the effects of contemporaneous/first-week/etc. entry of the second cohort (those that saw entry at age $a = 6$).

"treatment effects" of Amazon entry on Amazon outcomes.[19] In our final results, we often impose common treatment effects across groups of cohorts and/or weeks of treatment.[20]

We test the parallel trends assumptions in the analysis of each of our outcome variables. We do so by augmenting equation (1) with pre-treatment "proxy" treatment effects as follows:

$$\begin{aligned} y_{imt} \quad = \quad & \eta + \gamma_i + \gamma_m + \gamma_a + \gamma_t + \textstyle\sum_{r=5}^{A} \sum_{s=-W_{pre}}^{-1} \tau_{rs}^{parallel} * d_{i,AmEntry_i=r} * d_{a=r+s} \\ & + \textstyle\sum_{r=5}^{A} \sum_{s=0}^{W} \tau_{rs,3P} * d_{i,AmEntry_i=r} * d_{a=r+s} + \epsilon_{imt} \end{aligned} \tag{2}$$

where $\tau_{rs}^{parallel}$ are "proxy" treatment effects that measure differences in pre-treatment trends between the treatment and control groups, $W_{pre}(=20)$ is the number of pre-treatment weeks over which we test for trends, and we estimate post-treatment effects only for third-party outcomes.[21] Letting $\hat{\tau}_s^{parallel} = \frac{1}{N_r}\sum_r \hat{\tau}_{rs}^{parallel}$, $s = -W_{pre}, \ldots, -1$, with N_r be the number of separately estimated cohort effects, the test of the parallel trend assumption is the joint test, $H_0 : \tau_s^{parallel} = 0, \forall\ s = -W_{pre}, \ldots, -1$.

3.2.2 Effects of Amazon entry into existing products on prices and quality

We begin our analysis of the effects of Amazon entry into existing products with an analysis of consumer outcomes: prices and quality.

Prices For prices, we distinguish between Amazon's (post-entry) price for a product and average third-party merchant prices for that product, $m \in \{Am, 3P\}$. For product i in week t, prices are given by p_{imt} when $m = \{Am\}$ and by $\bar{p}_{imt} = \frac{\sum_z q_{z,imt} p_{z,imt}}{\sum_z q_{z,imt}}$ when $m = \{3P\}$, where z indexes the individual sales of product i by all third-party merchants in week t, $q_{z,imt}$ is the number of units sold in transaction z, and $p_{z,imt}$ is the price paid per unit in that transaction. All prices are inclusive of taxes and shipping charges. To foster convenient comparison of prices across many products, for any given product we normalize third-party prices by the average of $\bar{p}_{imt}$ for the 10 weeks pre-Amazon entry (or all pre-entry weeks if Amazon entered between 5 and 10 weeks of a product's "birth") and measure 3P merchant's (and Amazon's) price relative to this pre-entry average. For products in which Amazon did not enter, we normalize third-party prices by their full-sample average. We denote these pre-entry/no-entry average prices $\bar{p}_{i,3P}^{pre-entry}$. For reasons of confidentiality, we are not able to provide a table of summary statistics for prices, nor for the other outcome variables we analyze in the paper.

[19] All of our qualitative results across our outcome variables continue to hold when we estimate the model including treatment effects only for third-party outcomes.

[20] We also do not make any accommodations for right-censoring in our final results.

[21] That is, the equation substitutes $\tau_{rs,m}$ with $\tau_{rs,3P}$, as Amazon has no pre-treatment outcomes prior to their own entry.

As discussed above, the control group in our staggered difference-indifference analysis consists of products in which Amazon did not enter as well as pre-entry product-weeks for products in which Amazon did enter. For computational convenience, we also drop all products whose "lifetime" on Marketplace was less than one year.[22]

We begin our price analysis by estimating Equation (2) with $y_{imt} = \bar{p}_{imt}/\bar{p}_{i,3P}^{pre-entry}$ for $m = \{3P\}$ and $y_{imt} = p_{imt}/\bar{p}_{i,3P}^{pre-entry}$ for $m = \{Am\}$. The left panel of Figure 7 reports the average (across product age at entry cohorts) treatment effect of Amazon entry on average third-party normalized prices, $\hat{\tau}_{s,3P}^{parallel}$ and $\hat{\tau}_{s,3P}$, for two-week treatment windows between 20 weeks pre-Amazon entry and 40 weeks post-Amazon entry.[23] There is no evidence of violations of the parallel trends assumption and evidence of a statistically significant reduction in prices of approximately 3% from week 10 after Amazon entry. The right panel of Figure 7 indicates that these averages mask significant heterogeneity in treatment effects across age cohorts. Reported there are comparable average across-cohort treatment effects by groups of cohort weeks (with Amazon entry in 5-24, 25-49, 50-99, and 100+ weeks since a product's birth).[24] The strongest effects of an impact of Amazon entry on 3P prices comes from entry into *relatively young* products: there is clear evidence of significant price reductions for Amazon entry into cohorts in a product's first 5-24 weeks of life (when Amazon chooses to enter such products), but much more modest effects (if any) from Amazon entry into older products. There is also a common pattern across time: whatever price effects arise tend to happen within the first 10-15 weeks and remain (roughly) stable for the 40 weeks we investigate.

Figure 8 reports average (across product age at entry cohorts) treatment effect estimates from equation (1) for third-party and Amazon prices, $\hat{\tau}_{s,3P}$ and $\hat{\tau}_{s,Am}$, on the same figure and as well as comparable across average across-cohort "treatment effects," $\hat{\tau}_{s,Am}$, by age at entry cohorts. The left panel of Figure 8 shows that Amazon enters at a price almost five percentage points above the average pre-entry third-party price, but that their prices decline quickly into the 10th week post-entry before settling into a discount relative to the average pre-entry 3P price of 4-7%. The right panel of the same figure shows that these price advantages are also largely concentrated in those products in which Amazon entered early in its lifetime. The first two columns of Table 3 summarize the results for both average third-party and Amazon prices by estimating separate common-within-age-at-entry-cohort treatment effects by these four cohorts for both groups, confirming that Amazon entry into young cohorts is associated with a 5.6% reduction in average third-party prices, a 6.3% reduction in Amazon's own price, and a small number of more modest effects for both 3P and Amazon prices in later cohorts. Before interpreting these findings (in Section 3.2.4 below), we

[22]This represents 42.2% of products, but only 3.5% of in-sample revenue.

[23]For computational reasons, we estimate with flexible treatment effects pre- (testing the parallel trends assumption) and post-entry using two-week instead of one-week windows.

[24]A test of the (linear) parallel trends assumption cannot be rejected for each cohort.

first present our results for other outcome variables.

We also explored the extent of heterogeneity in treatment effects across different Home & Kitchen product types. Our data includes fields for a product's Category (c) and Subcategory (s). There are 467 of the former and 2,531 of the latter, although some products (covering 10.2% of in-sample revenue) have no listed subcategory and many have few sales. Relying on the 300 largest subcategories by sales, Figure 9 reports the estimated common-within-age-at-entry treatment effects for average third-party and Amazon prices for each subcategory for each of these four entry cohorts. The distributions tend to be similar, with both showing heterogeneity in the effects of Amazon entry, but with the majority of the mass centered on the across-subcategory coefficient estimates reported in Table 3. As the computational burden of estimating so many subcategory $\times$ age-at-entry cohort treatment effects is high, we do not report comparable results for the remaining outcomes in this subsection.

Quality (Availability) There are many potential indicators of a product and/or merchant's quality of service. In an online retail environment, product availability, shipping time, and a product's condition on arrival (i.e. Is it the correct product? Is it undamaged?) are all material to a customer's shopping experience. Of these, we were able to obtain data on third-party product availability, an outcome previously studied in the context of the competitive effects of Walmart entry (Matsa 2011).[25]

Under Marketplace rules, sellers are not allowed to list products that they do not have in stock (and are thus not available). We observe availability at the product-merchant level using the amount of stock each merchant reports to Amazon at the end of each day.[26] We use this to determine, for each product, if it was available for some third-party merchant on each day in the data and then average this across days for our weekly analysis, which we call $avail_{imt}$ for $m = \{3P\}$. As for prices, to foster convenient comparisons across many products that may differ in their baseline availability, we normalize each product's average availability by the average of $avail_{imt}$ for the 10 weeks pre-Amazon entry, which we call $\bar{avail}_{imt}$. Unfortunately, this measure is only reliably available for third-party merchants and not for Amazon itself, so we are not able to compare Amazon's post-entry availability to a product's pre-entry average.

To measure the impact of Amazon entry, we therefore estimate a version of Equation (2) with $y_{imt} = \bar{avail}_{imt}$. As for prices, the left panel of Figure 10 reports the average (across cohorts) treatment effect of Amazon entry on average third-party availability for two-week treatment windows between 20 weeks

[25]Shipping locations are specific to a product and customer and we did not have access to any customer-level data. Even had we had the data, shipping times, like a product's condition on arrival, are seller-specific. Third-party sellers do have ratings on Amazon.com, but Amazon does not keep historical metrics of seller ratings and the time and computational cost of reconstructing them at the time of each sale was prohibitive.

[26]Amazon collects offer information for each product on Marketplace at the end of each day.

pre-Amazon entry and 40 weeks post-Amazon entry.[27] Treatment effects can be interpreted as the estimated percentage change in average third-party prices relative to their pre-Amazon-entry average.

There is evidence of a statistically significant increase in availability associated with Amazon entry. The right panel in the same figure show that, also as for prices, there is heterogeneity in treatment effects across cohorts, with the estimated increase in availability concentrated on *relatively young* products and, if anything, decreases in availability for older cohorts. The third column in Table 3 summarize these results, confirming that Amazon entry into young cohorts is associated with a 11.3% increase in average third-party availability, with significant negative effects (of 5.3% and 4.6%) of Amazon entry on average third-party availability in older cohorts. The latter results are perhaps surprising, but could reflect a strategic response of third-party merchants to facing a more efficient competitor. We discuss further the impact of third-party product availability on Amazon's choice of products to enter in Section 4 below.

3.2.3 Effects of Amazon entry into existing products on revenue, quantity, and active merchants

We turn next to the topics core to the policy debate: the effects of Amazon entry on third-party merchant outcomes, including revenue, quantity, and net entry/exit, which we measure by the number of active merchants. In this subsection, we look at these topics in the context of entry into existing products; in subsection 3.4.2 below, we broaden our horizons to examine effects of Amazon Private Label entry on substitute products.

Revenue and Quantity While conceptually the same, we modify the specifics of our estimation approach to account for the frequent presences of zeros in our revenue and quantity data. In particular, we adapt Equations (1) and (2) into an exponential regression model and estimate them by Poisson quasi-Maximum Likelihood Estimation; they are otherwise identical to the specifications considered above. Thus we specify the expected value of revenues or quantities as an exponential function and select the parameters to maximize the likelihood of seeing those revenues and quantities that we see in the data:

$$E[y_{imt}|x] = \exp\left(\eta + \gamma_i + \gamma_m + \gamma_a + \gamma_t + \sum_{r=5}^{A}\sum_{s=0}^{W} \tau_{rs,m} * d_{i,AmEntry_i=r} * d_{a=r+s}\right) \tag{3}$$

where the definitions of each of the parameters is as described under Equation (1) above.[28] Given the

[27] All of our regression results, weight each product by its total (Amazon + total 3P) average per-week in-sample revenue. This ensures that the effects of entry that we measure are representative of the economic importance of their impact.

[28] The comparable equation when testing pre-treatment trends is:

$$\begin{aligned} E[y_{imt}|x] &= \exp\Big(\eta + \gamma_i + \gamma_m + \gamma_a + \gamma_t + \textstyle\sum_{r=5}^{A}\sum_{s=-W_{pre}}^{-1} \tau_{rs}^{parallel} * d_{i,AmEntry_i=r} * d_{a=r+s} \\ &\quad + \textstyle\sum_{r=5}^{A}\sum_{s=0}^{W} \tau_{rs,3P} * d_{i,AmEntry_i=r} * d_{a,AmEntry_i=r+s}\Big) \end{aligned} \tag{4}$$

new functional form, the interpretation of the parameters changes slightly as well: $\tau_{rs,m}$ (approximately) measures the proportionate change in expected revenues or quantities for merchant type m (3P or Am) when, for age cohort r, the product is in the s^{th} week after Amazon entry.[29]

For both revenues and quantities, we distinguish between Amazon's (post-entry) revenue or quantity for a product and the total third-party merchant revenue or quantity for that product, $m \in \{Am, 3P\}$. Thus for product i in week t, revenue and quantity are given by rev_{imt} and qty_{imt} when $m = \{Am\}$ and by $rev^{Tot}_{imt} = \sum_z q_{z,imt} p_{z,imt}$ and $qty^{Tot}_{imt} = \sum_z q_{z,imt}$ when $m = \{3P\}$, where z indexes the individual sales of product i by all third-party merchants in week t, $q_{z,imt}$ is the number of units sold in transaction z, and $p_{z,imt}$ is the price paid per unit in that transaction. All prices are inclusive of taxes and shipping charges. Unlike for prices, we do not normalize the revenue and quantity data, relying instead on product fixed effects to account for heterogeneous revenue and quantity levels across products and the exponential functional form to foster convenient interpretation of the coefficient estimates (cf. footnote 29 above). The sample of data for the revenue and quantity regressions is the same as described above for the price regressions, but for the additional presence of zeros in the revenue and quantity data when there are no sales.[30]

As for prices, we begin our revenue and quantity analyses allowing for non-parallel trends by estimating Equation (4) with $y_{imt} = rev^{Tot}_{imt}$ and $y_{imt} = qty^{Tot}_{imt}$ for $m = \{3P\}$ and $y_{imt} = rev_{imt}$ and $y_{imt} = qty_{imt}$ for $m = \{Am\}$. The two left panels of Figure 11 reports the average (across product age at entry) treatment effect of Amazon entry on total third-party revenues and quantities, $\hat{\tau}^{parallel}_{s,3P}$ and $\hat{\tau}_{s,3P}$, for two-week treatment windows between 20 weeks pre-Amazon entry and 40 weeks post-Amazon entry. There is no evidence of violations of the parallel trends assumption for either outcome variable, nor is there evidence of a significant effect (across cohorts) of Amazon entry. As for prices, however, these averages mask significant heterogeneity across age cohorts. The two right panels of Figure 11, while variable, show a general pattern of increases in revenue and quantity when Amazon enters into young (5-24 and 25-49) cohorts and a pattern of no change or a slight decrease in revenue and quantity when Amazon enters into older (50-99 and 100+) cohorts.

Figure 12 reports treatment effect estimates from equation (3) for third-party and Amazon revenues and quantities on the same figure.[31] The left-hand panels aggregate across age cohorts while the right-hand

[29] Formally the proportionate effect is $(\exp(\tau_{rs,m}) - 1)$, but this is close to $\tau_{rs,m}$ for values of $\tau_{rs,m}$ close to zero. As our estimated values of $\tau_{rs,m}$ are often quite far from zero, we present proportionate effects in tables using the exact formula.

[30] We include such zeros between weeks of non-zero sales, but drop them after all third-party merchants exit the product, whose date we define as the week of their last sale (similarly for Amazon).

[31] The estimated treatment effects on 3P revenues and quantities in the left-hand panels of Figures 11 and 11 differ only in the reference period against which they are measured. In Figure 11, they are measured relative to $t-1$, the week before Amazon entry; In Figure 11 they are measured relative to the full 20 pre-entry weeks.

panels report the cohort-specific "treatment effects" across cohorts (analogous to the right-hand panels in Figure 11 showing treatment effects on total 3P revenue and quantity). A clear pattern emerges: Amazon entry into the youngest cohort (aged 5-24 weeks) is associated with their (Amazon) earning revenue comparable to that earned by third-party merchants in total (though with no decrease to 3P merchant revenue), whereas entry into later cohorts is associated with their earning a small fraction of pre-entry total 3P revenue.[32] Table 4 summarizes the results for both average third-party and Amazon revenues and quantities by estimating separate common-within-age-at-entry-cohort treatment effects by these four cohorts for both groups, confirming that Amazon entry is associated with no statistically significant effect on either revenues or quantities in any 3P product age cohort, and that the only statistically significant effects in the data are that Amazon tends to earn a very small fraction (3-7%) of pre-entry total third-party revenues or quantity. As for prices, we defer a thorough interpretation of these patterns until Section 3.2.4 below.

Number of Active Merchants (Net Entry and Exit) We turn next to the impact of Amazon entry on net entry and exit within individual products, measured by the number of (quarterly) "active" third-party merchants selling that product. Quarterly-active merchants are defined, for any given quarter, as those merchants, ranked by sales, that contribute to 90% of a product's sales in that quarter. Amazon is often but not always an active merchant; we nonetheless always include them when they are present selling a product. We define active merchants for each product to focus our analysis on those merchants that represent the strongest competitors offering that product, though we note that all of the qualitative results in this section are robust to using all merchants that made a sale rather than active merchants. A merchant is "ever active" in a product if it is "quarterly active" in any quarter in the life of that product.

Our estimating equations are the same as Equations (1) and (2) used to measure the effects of Amazon entry on third-party prices. As for all previous outcomes, we distinguish between Amazon's (post-entry) presence selling a product and the total number of active third-party merchants selling that product. Thus for product i in week t, $m = \{Am\}$, $y_{imt} = Amazon_{imt}$, a dummy variable indicating that Amazon is active selling product i in week t, and, when $m = \{3P\}$, $y_{imt} = ActMerchs^{Tot}_{imt} = \sum_n QuarterlyActiveMerchant_{int}$, the sum of the number of quarterly active merchants, n, offering product i in week t. For any given product for which a merchant is ever active, we define entry as the first week in the data in which a merchant makes a sale and exit as the final week in the data in which a merchant makes a sale; this allows merchants to continue to be "active" even if they make no sales in given week (a common occurrence with rarely-sold products). We again don't normalize the number of active merchants, but instead include product $\times$ merchant fixed

[32] To help interpret the magnitudes of the reported effects, values of $\hat{\tau}_{rs,Am}$ in the range of -4.0 to -2.5 are associated with revenues of 1.8% to 8.2% that of total pre-entry third-party revenue.

effects so that the regression results report, for third-party merchants, the change in the number of active merchants relative to the number present prior to Amazon's entry and, for Amazon, the share of products in which it continues to sell instead of exiting.

The two left panels of Figure 13 reports the average (across product age at entry cohorts) treatment effect of Amazon entry on the number of active third-party merchants, $\hat{\tau}_{s,3P}^{parallel}$ and $\hat{\tau}_{s,3P}$, for two-week treatment windows between 20 weeks pre-Amazon entry and 40 weeks post-Amazon entry. There is weak evidence of violations of the parallel trends assumption and a small but statistically significant correlation with net entry post Amazon entry. As ever, these averages mask significant heterogeneity across age cohorts. The two right panels of Figure 13, show a clear pattern of third party net entry when Amazon enters into young (5-24 and 25-49) cohorts and slight net entry or slight net exit when Amazon enters into older (50-99 and 100+) cohorts.

Figure 14 reports treatment effect estimates from equation (1) for third-party active merchants and Amazon (whether active or not) on the same figure. The left-hand panel aggregates across age cohorts while the right-hand panel report the cohort-specific Amazon "treatment effects" across cohorts. A surprisingly consistent pattern emerges: Amazon often exits quickly those markets it chooses to enter, with exit rates after 40 weeks similar across product ages (at a level between 35-45% after 40 weeks). The third set of columns in Table 4 summarizes the results for both active third-party merchants and Amazon, confirming that Amazon entry is associated with a statistically significant amount of net entry in the youngest age cohort and slight net exit in the oldest cohort and statistically significant 40-week exit rates of 35-40% across all cohorts.

3.2.4 Effects of Amazon entry into existing products: Interpretation

In this section, we interpret our estimated effects of Amazon entry on consumer and third-party merchant outcomes. We first note that, despite using methods designed to estimate causal effects, Amazon entry is clearly correlated with unobserved demand shocks that are observed by third-party merchants (and presumably Amazon), at least for the youngest Amazon entry cohorts (i.e. when Amazon enters in weeks 5-24 of a product's life). This can be seen most clearly in the first row of impacts in Tables 3 and 4: Amazon entry is associated with statistically significant increases in the number of third-party active merchants, increases in total (3P + Amazon) product revenue and quantity,[33] and statistically significantly falling prices. The figures underlying these regression results visually support the likelihood of early Amazon entry being associated

[33] As there is no reduction in total 3P revenue upon Amazon entry and Amazon's own revenue upon entry is approximately equal to that of pre-entry 3P merchants, total revenue upon Amazon entry roughly doubles.

with positive unobserved (by us as econometricians) demand (and competition) shocks.[34]

Patterns for other age cohorts, particularly those older than 50 weeks, are more likely to satisfy the conditions for causal effects interpretation, but even here one cannot be certain.[35] To the extent that the results summarized above are consistent with unobservable positive demand shocks at the beginning of a product's lifespan, there is also the risk for unobserved negative demand shocks for long-lived products (and these may not be known to Amazon). That being said, there are few economically large or significant effects in the Home & Kitchen in Germany data that we study: Amazon frequently exits markets that it enters, often quickly, and when it stays this is sometimes associated with slightly lower prices for existing third-party merchants and itself. It does not, however, appear to drive out a meaningful share of third-party sales (measured in quantity or revenue), and itself achieves on average single-digit revenue shares in the products that it enters. While these small shares may add up to a meaningful amount of revenue in the aggregate, the evidence summarized here does not support claims in policy circles of widespread expropriation of third-party revenue, but instead suggests that Amazon entry into existing product markets is rather more associated with (mild) market expansion than with business stealing.

3.3 Effects of Amazon entry into existing products on new product introductions

The policy debate on Amazon entry raises concerns not only about the short-run effects of Amazon's entry into third-party merchant products, but also on longer-run effects of Amazon's entry on third-party merchants' incentives to introduce innovative new products. In particular, does the possibility and/or the practice of Amazon entry deter third-party merchants from selling new products on Marketplace for fear that Amazon will later simply enter and sell the same or similar products.

To address this question, we examine the effects of Amazon entry into one of the products a third-party merchant sells on the *overall* activities of that merchant. Given the tenor of the debate above, we define our outcome of interest the introduction of "single-merchant" new products by third-party merchants.[36] Our

[34]Note in particular that there is an increasing trend pre-Amazon-entry in number of active merchants and revenues for the youngest age cohorts.

[35] The purpose of this project is to establish whether the raw patterns in Germany's Amazon Marketplace data are consistent with the policy concerns regarding negative consumer and/or merchant effects of Amazon's business practices, and not to estimate the causal effects of Amazon entry on consumer and/or merchant outcomes. That being said, we selected an empirical methodology that has proven effective in estimating causal effects in a wide variety of settings. During the course of this research, we learned that the empirical environment revealed by Marketplace data is more complicated than many, with significant product life-cycle (thus dynamic) effects and heterogeneity across products, merchants, age, and time. We attempted to control for these effects in the first instance with (product) age dummies, and even explored, for some of our outcome variables, separate age dummies for cohorts of products depending on their age at Amazon entry, but the qualitative results above were unchanged. Researchers interested in estimating the causal effects of Amazon entry with similar data will need to think carefully about how to adequately control for strongly heterogeneous product life-cycle effects (among other possible sources of endogeneity) when conducting their analyses.

[36]As described above, we define single-merchant new products as a product who makes sales from only one merchant in the first four weeks of its life. This distinguishes it from multi-merchant new products, where 2 or more merchants make sales in these first

estimation sample focuses on those merchants that are most active on Marketplace, and on the products in which they are themselves most active. We therefore include all "ever active merchants," i.e. merchants which ever contributed to 90% of a Marketplace product's sales in at least one quarter of our data and analyze the impact of entry of Amazon only into those products for which a merchant was ever active.

Given the importance of innovation effects in the current policy debate, we benchmark our analysis of the effects of Amazon entry against those of merchants likely to be of similar efficiency. For simplicity, we assume that the largest third-party merchants by revenue are those most likely to satisfy this criterion and define a "big third-party merchant" as one of the top 100 third-party merchants by revenue in the Home & Kitchen department in our sample period. We denote these "Big 3P" merchants, with the remaining third-party merchants referred to as "Fringe 3P" merchants.[37]

We adapt the econometric specification used throughout our product-level analyses in the previous subsections to suit a merchant-level analysis. First, as above, we divide our merchants into "Big 3P" versus "Fringe 3P" and then measure the effects of the first entry of either Amazon or one of the big third-party merchants (whoever was first to enter) on the rate of new product introductions of fringe third-party merchants:

$$\begin{aligned} NumNewProds_{gmt} = \eta + \gamma_m + \gamma_{ma} + \gamma_t + \sum_{s=0}^{W} \tau_s^{Am} * d_{m,AmFirst_m=t-s} \\ + \sum_{s=0}^{W} \tau_s^{Big3P} * d_{m,Big3PFirst_m=t-s} + \epsilon_{mt} \end{aligned} \tag{5}$$

where $NumNewProds_{gmt}$ is the number of single-entry new products introduced by fringe 3P merchant m of growth type g (defined below) in week t, γ_m, γ_{ma}, and γ_t are merchant, merchant age, and time (week) fixed effects, τ_s^{Am} is the estimated treatment effect of Amazon's first entry into one of merchant m's products in week s after Amazon entry, $d_{m,AmFirst_m=t-s}$ is a dummy equal to 1 if a product sold by merchant m was first entered by Amazon (instead of a Big 3P merchant) and first saw Amazon entry within s weeks previous to the current week t, where $s = 0, \ldots, W$, with $W = 80$.[38] τ_s^{Big3P} and $d_{m,Big3PFirst_m=t-s}$ are similarly defined for those merchants that first experienced Big 3P entry. In the estimation sample (described more fully below), merchants first experiencing Amazon entry earned 20.9% of in-sample revenue, those first experiencing Big 3P entry earned 6.7% of revenue, and the remaining merchants experience no in-sample

four weeks (as might arise, for example, when a manufacturer releases a new product and that is introduced and sold on marketplace by multiple sellers).

[37]Big third-party merchants as defined account for approximately one-third of total third-party revenue in the Home & Kitchen department in this period.

[38]When $s = 0$, this will indicate the week of entry; when $s = 80$, this will indicate the last week over which we estimate the effects of Amazon's entry. In the analysis here, we focus on Amazon's first entry into a merchant's existing product mix, covering 55% of the Amazon entry cases (with the remaining merchants seeing two or more instances of Amazon entry).

Amazon or Big 3P entry.[39]

The policy debate focuses on the potential impact of Amazon entry on third-party merchants' incentives to offer innovative new products on Marketplace and our analysis therefore seeks to measure these effects, and to benchmark them against effects of other efficient (Big 3P) seller entry. To do so, we must first distinguish between "innovative" and "non-innovative" products. We do so by segmenting products according to their revenue growth over their (pre-Amazon and/or pre-Big-3P entry) lifespan.[40] For each product, we define its revenue growth rate at the quarterly level over its lifetime. Restricting attention to those products whose lifetimes are at least one year, we define "high-growth" products as those with a mean and median revenue growth rate above 1, "low-growth" products as those with a mean growth below 1, but median growth above 1, and "no-growth" products as those with those with both mean and median growth below 1.[41] These definitions are arbitrary, but Table 5 shows that, when evaluated across the full sample, they segment well Marketplace products, with the top three groups constituting roughly two-fifths of the products but almost 90% of the revenue in the Home & Kitchen department. Figure 15 reports the time pattern of revenue by each product growth type in the Home & Kitchen department in our sample.

In what follows, we define innovative products to be our "high-growth" products, capturing 11.3% of products but 45.8% of revenue in the Home & Kitchen department. We measure the effects of the first Amazon or Big 3P entry into any Fringe merchants' existing products, not just those that may have been high growth.[42] As we are particularly interested in the effects of such entry on "innovative merchants," we analyze the effects of such entry separately for merchants depending on their history of successful (i.e. high-growth) new product introductions. In the Home & Kitchen department for the sample which allowed us to measure all the key covariates in this analysis, 96.9% of merchants, covering 85.4% of revenue, had introduced no pre-Amazon-or-Big-3P-entry high-growth new products (including those merchants that never saw such entry), 2.1% of merchants, covering 6.7% of revenue, had introduced one such new product, and 1.0% of merchants, covering 8.0% of revenue, had two or more such new products.[43] Table 6 reports the average number of new product introductions by these three merchant pre-entry product growth segments, for both

[39]Note that this doesn't mean that such merchants never competed against Amazon in our data. They may have experience Amazon entry before week 5 (such events are excluded from of the estimation sample) or entered an ASIN in which Amazon was active.

[40]The average age at which a fringe merchant first experiences entry into one of its products is similar, albeit slightly less, for first Big 3P relative to first Amazon entry.

[41]There are three other categories in the data: "short exit" products/merchants are those that exist for less than a year, "instant exit" products/merchants are those that exist for less than a quarter, and the remaining products are too new to Marketplace to calculate our growth measures, making up a residual, "not enough data," category.

[42]We explored also estimating the effects of entry into high-growth products but the data were not rich enough to detect any significant correlations.

[43]This analysis measures the effects of Amazon and Big 3P entry on over 52,000 merchants. To be included in the sample, we required four quarters of revenue data to calculate product growth types (thus the last year is dropped), a new product had to survive at least one year, and we had to be able to calculate the age of the merchant. This sample captures 55.6% of the full sample revenue.

high- and non-high-growth product introductions and by pre/post entry period (if relevant). The patterns in our subsequent regression results are qualitatively similar to those in this table of data patterns.

In our analysis, we estimate versions of Equation (6) for each of three dependent variables: the number of all single-entry new products as well as the number of high-growth and non-high-growth single-entry new products. This allows us to capture the impact of Amazon entry on the introduction of (what turns out to be) both innovative and non-innovative new products. The left panel of Figure 16 reports average treatment effects of the first Amazon entry into one of a merchant's products on the number of subsequent single-entry new products introduced by merchants between 20 weeks pre-Amazon entry and 80 weeks post-Amazon entry. In the right panel, we examine the heterogeneity in this treatment effect across the number of previous high-growth single-entry new products a merchant had introduced previous to Amazon entry. There is a slight positive relationship for merchants with 0 previous high-growth new products, no effect for those with 1, and strong negative effects for those with two or more such products.[44]

Table 7 reports regression results from a version of Equation (6) which imposes common effects of Amazon and Big 3P entry across weeks, but allows τ to vary by the number of each merchant's pre-Amazon-entry or pre-Big-3P-entry single-entry high-growth new products introduced, both for all such new products as well as broken out by (what turned out to be) high-growth and non-high-growth new products. The results show negative relationships between Amazon and Big 3P entry and third-party merchants' subsequent new product introductions, with statistically significant correlations for Amazon entry on merchants with two or more previous high-growth new product introductions and for Big 3P entry on merchants with one previous high-growth new product introduction. Comparing to the average number of weekly pre-entry new product introductions in Table 6, the magnitudes of the relationships are large, with effect sizes among those with positive pre-entry high-growth new product introductions generally in the range of 40-80%. Absolute effect sizes are more negative for Big 3P than Amazon entry, as (generally) are relative effect sizes.

The goal of our analysis in this section has been to provide empirical evidence on important policy concerns surrounding the impact of entry of marketplace owners in hybrid platform markets on innovation on the platform. As highlighted in the introduction, some have argued that hybrid platforms present an inherent conflict of interest that is prone to innovation-reducing imitation (House Judiciary Committee's Antitrust Subcommittee 2020). The economics literature provides more nuanced conclusions, however, with both Hagiu et al. (2020) and Madsen and Vellodi (2021) showing that a forward-looking hybrid platform has an incentive to internalize the innovation-reducing effects of its entry on the long-run value of the platform. A platform following such a strategy must necessarily balance the increased value to consumers and the

[44] We tested the assumption of parallel linear pre-trends for each of these cohorts and could not reject it for any.

platform of entry in competition with third-party sellers against the loss of innovation from sellers who respond to such imitation by failing to bring future new products. Hagiu et al. (2020), in particular, find a platform internalizing such effects is more likely to imitate less innovative products.

How then to interpret our results? Unfortunately, we do not think that they reveal the causal effects described in this literature and instead simply reflect "reversion to the mean" in new product introductions. In particular, having a successful new product introduction is uncertain. While there may be persistence in the ability to successfully identify, market, and ultimately sell some new products (e.g. for brand owners introducing a new version of a previously successful product), this certainly isn't true for all new products. Thus for merchants that have previously introduced a successful new product, we would expect a downward trend in the expected success rate of subsequent product introductions and, by backward induction, a lesser desire to introduce new products in the first place, with the oppositive effect for those merchants that have not previously introduced a successful new product. Furthermore, since our entry analysis analyzes the effect of a merchant's first exposure to Amazon or Big 3P entry, entry is necessarily increasing over time. Thus our estimated correlations between new product introductions and entry likely capture correlations between a decreasing (for previously successful merchants) or increasing (for previously unsuccessful merchants) trend in new product introductions and an increasing trend in Amazon or Big 3P entry in the raw data. Correctly measuring the causal effects of entry on innovation on Amazon Marketplace would need to address such considerations, as well as the life-cycle patterns that threatened identification in the previous subsections (cf. footnote 35). Attempting to do so is beyond the scope of this study, but a highly interesting area for future research.

3.4 Cross-product effects of Amazon entry, including Private Label entry

We turn now to the more challenging case of assessing the effects of Amazon's entry into one product on other products. The increased challenge arises from the difficulty defining appropriate groups of substitute products over which to measure effects for the more than 100,000 Home & Kitchen products in our dataset.

We seek to resolve this challenge in two ways. First, we analyze general cross-product effects of entry within individual Home & Kitchen subcategories. Subcategories on Marketplace are mutually exclusive and exhaustive and capture meaningful and intuitive differences between products. Second, given their importance in the policy debate, we use Amazon search results to define substitute products for each of the largest Amazon's Private Label kitchen products and measure the effects of Private Label entry on these substitutes. We describe each exercise in turn.

3.4.1 Cross-product effects within subcategories

Amazon classifies the thousands of products in the Home & Kitchen department into 467 categories (e.g. Vacuum cleaners, Kettles, Fans) and over 2,500 subcategories (e.g. Robotic vacuum cleaners, Stick vacuum cleaners, Cylinder vacuum dust bags, etc.). Table 8 reports the top 10 subcategories by revenue in the Home & Kitchen department as well as, for each subcategory, the number of "active" products, defined as the set of products that make up 90% of the revenue within that subcategory in our sample period, the number of Amazon Private Label products, and the number of "active" entry events, defined as entry by an ever-active merchant into one of the active products.[45]

To measure cross-product effects of entry, we estimate reduced-form regressions of the following form:

$$\begin{aligned} \log(1+y_{st,m}) \quad &= \quad \eta + \gamma_s + \gamma_t + \textstyle\sum_n \gamma_{mn} \log(1+entries_{st,n}) + \gamma_{tot} \log(1+products_{st}) + \epsilon_{st,m}, \\ & m,n = \{Big3P, Fringe3P, Amazon\} \end{aligned} \tag{6}$$

where $\log(1+y_{st,m})$ is the log of (one plus) a revenue variable (to be further described) earned by all products in subcategory s in week t, m indexes three types of merchants, big third-party merchants ("Big3P"), other third-party merchants ("Fringe3P"), and Amazon, γ_s and γ_t are subcategory and week fixed effects, $\log(1+entries_{st,n})$ is the log of one plus the number of products that entered subcategory s in week t ,$n \in Amazon, Big3P, Fringe3P$, and $\log(1+products)_{st}$ is the log of (one plus) the total products offered in subcategory s in the Home & Kitchen department in week t. Our estimation sample relied on 2,225 subcategories with complete data covering 90% of the revenue among products that had a subcategory.

In what follows, we report specifications with two different outcome variables, $\log(1+y_{st,m})$. [46] We report results for both (i) $\log(1+revenue_{st,m})$, which is, for each merchant type, m, the log of (one plus) the total revenue of all of products in subcategory s in week t and for (ii) $\log(inc\_rev_{st,m})$, the log of the total revenue of all *incumbent* products of merchant type m in s and t, where incumbent revenue excludes revenue from all products of that merchant type that entered that subcategory in the previous 80 weeks. We also report regression results aggregating each revenue variable across all merchant types, yielding a total subcategory-level revenue measure. We exclude the first 80 weeks of a subcategory's life from our analysis to ensure we are measuring the effects of *de novo* entry in each subcategory.

The purpose of these regressions is to try to answer "from whom do new entrants steal revenue?" The iden-

[45]Ever-active merchants, defined above, are those that contribute to 90% of the sales of that product in some quarter in our sample period.

[46]Including "1+" in the specifications was for computational convenience. We care most about relative rather than absolute magnitudes of the coefficients. As such, we determined this a convenient parameterization.

tification strategy is similar to an aggregated version of that used in the within-product analysis above: to exploit variation in the number and timing of entry of new products on the total and incumbent revenues of Amazon, Big 3P, and Fringe 3P merchants. We include subcategory level fixed effects to pick up unobserved differences in demand or competitive conditions across subcategories and date fixed effects to pick up seasonality or other time-varying shocks for the Home & Kitchen department as a whole. One threat to our identification strategy would be the presence of time-varying demand shocks, e.g. from demand growth within a subcategory. In this case, more product entry could be correlated with positive demand shocks and could cause an upward bias in our parameter estimates. Another is that subcategories could include products that aren't fully substitutable. While we think product complementarity is unlikely given the granularity of subcategory definitions (c.f. those listed in Table 8), there are many products in each subcategory and they may not all be close substitutes. This mixing of more and less substitutable products would tend to attenuate our estimated effects. By the same token, if products substitute across subcategories (e.g. Robotic and Stick vacuum cleaners), then we may underestimate the extent of business stealing between merchants. Despite these concerns, each of these considerations would seem to apply equally across merchant types, thus our estimates should at minimum provide insights on the relative effects of each type of merchant entry on own and rivals' subcategory revenue.

Table 9 presents our results. Focusing first on the upper half of the table, the upper-left panel reports the coefficient estimates of regressions of log revenues of each merchant type (as well as total subcategory revenue) on the log number of new entrants of each revenue type, as well as a control for the number of products in the subcategory. Patterns are broadly in line with expectations: entry of, e.g., 10% more big third-party products in the previous 80 weeks are associated with a 4.7% increase in big third-party revenue in week t. Diagonal elements are uniformly positive and the elasticity of revenue with respect to increases in total numbers of products tend to be between 0.9 and 1.5.

The challenge with total revenue as the dependent variable is that entry induces both market expansion (due primarily to sales of the new products) as well (possibly) as business stealing (due to reduced sales of existing products). The upper-right panel of Table 9 seeks to isolate the business-stealing incentives by excluding from the dependent variable, revenue, all revenues from products that have entered in the previous 80 weeks. Thus the dependent variable in any given week, t, which we call "incumbent" revenue, reflects revenue from products at least 80 weeks old as of t. The coefficients then measure the correlation of these incumbent revenues with more or fewer entrants in the previous 80 weeks of the various merchant types.[47]

[47]We choose not to control for total (incumbent) products in this specification as the number of incumbent total products in week t are fixed and variation over time would arise exclusively from product exit, which is not the focus of this exercise. That being said, the qualitative patterns in the table are the same when including such a covariate.

The results show more clearly cannibalization, at least for some merchant types. In particular, increases in fringe (big third-party) entry is associated with reductions in incumbent fringe (third-party) revenue. By contrast, increases in Amazon entry tend not to cannibalize anyone's sales, if anything being associated with a slight increase in big third-party revenue. Further confirming these patterns, a 10% increase in Amazon entry is associated with a 0.7% *increase* in total subcategory revenue (statistically significant at the 10% level), while a similar 10% increase in fringe third-party entry is associated with a 1.5% decrease in total subcategory revenue.

3.4.2 Effects of Amazon Private Label entry

We address the question of the effects of Amazon Private Label (PL) entry by combining the methods of the previous subsections: we define a set of substitute products over which to measure the cross-product effects of Private Label entry and then use methods similar to that in Section 3.2 to measure the effects of that entry on some of our earlier outcome variables (notably revenue and prices).

For each of the largest Private Label products in the Home & Kitchen department, we used Amazon's search results to identify substitute products. In particular, for each Private Label product, we asked Amazon to identify all searches in the first week of each month in our sample in which that Private Label showed up on the first "page" of search results (which they define as the top 20 results). We asked them to identify all other products that also showed up in the first page of results and then defined as potential substitutes all products in that list that were in the same Home & Kitchen subcategory.[48] To align the analysis to the policy concerns raised in this space, we selected the five highest-revenue products among these potential substitutes as our substitutes of interest, i.e. that were "treated" by Amazon Private Label entry. For the same reasons, we also focused our PL analysis on the 50 Home & Kitchen Private Labels with the highest revenues, for which we were able to construct a valid control group for 31.

We also use the search results to help define a set of control products for the set of substitute products treated by Amazon's PL entry. An ideal control group would control for unobserved demand and/or cost shocks common to the subcategory of PL entry but not affected itself by the entry of Amazon's PL product. Our choice is the set of all products within the PL entry subcategory that we did *not* show up in the search results described above. These products' absence in Amazon's search results supports the assumption that they are not a substitute for the Amazon PL product and their presence in the same subcategory supports the assumption that they may be subject to similar unobservable subcategory-level demand, cost, or competition shocks. On average across the PL products that we considered, 18.4% of the subcategory revenue came from

[48]This was important to eliminate complements, e.g. vacuum bags for Private Label vacuum cleaners (and vice versa).

the PL's treated group, 60.4% from the PL's control group, 1.7% from the PL itself, and the remainder from products below the top 5 that were included in Amazon search results with the PL.

We then estimated treatment effects specifications of the following form:

$$y_{jmt} = \eta + \gamma_j + \gamma_t + \sum_{r \in R} \sum_{s=0}^{W} \tau_{p(r)s,m} * d_{i,AmEntry_i=r} * d_{a=r+s} + \epsilon_{jt} \tag{7}$$

where y_{jmt} is an aggregate outcome of interest (e.g., average price or total revenue or quantity) of the products, i, defined to be part of the treated substitute products for Amazon Private Label product j, $i, \ldots, I_j$, for merchant type $m \in \{3P, Am\}$ in week t, γ_j and γ_t are Private-Label-related-product and time (week) fixed effects, $\tau_{p(r)s,m}$ is the estimated treatment effect of Amazon entry for the cohort group p (the average of the age at entry r_i for the treated substitutes, i, for Private Label product j) in week s after Amazon entry, with separate effects by merchant type m, $d_{i,AmEntry_i=r}$ is a dummy equal to 1 if product i saw Amazon entry at week r. The (average) "age at entry," r, for PL j is a sales-weighted average of the ages of the five substitutes for each PL j, and this average age at entry is allocated to one of three cohort groups, p, defined by $R = \{$5 - 49, 50 - 99, 100+$\}$, $d_{a=r+s}$ is an time dummy equal to 1 if in the s^{th} week after Amazon's (average) age at entry, where $s = 0, \ldots, W$.

There are several differences in this specification relative to those in Section 3.2, all related to the fact that we are measuring cross-product rather than within-product entry. First, the outcome variable of interest is an aggregate of the outcomes of the five treated products for each Amazon Private Label: for prices, it is the sales-weighted average price and for revenue and quantity it is the total revenue and total quantity. Second, since we measure the effect of Amazon's PL entry on five substitute products, there is no single age at entry; rather we calculate a sales-weighted average age at entry and measure effects across age cohorts relative to this average age.

The qualitative results for the effects of Amazon Private Label entry are quite similar to those shown above for within-product entry, so we present them briefly. The left panel of Figure 17 and the two left panels of Figure 18 report the treatment effect of Amazon PL entry on average third-party substitutes' prices and total third-party substitutes' revenue and quantity, $\hat{\tau}^{parallel}_{s,3P}$ and $\hat{\tau}_{s,3P}$, for two-week treatment windows between 20 weeks pre-Amazon entry and 40 weeks post-Amazon entry. The right panels of each figure overlay Amazon outcomes relative to average (for prices) or total (for revenue and quantities) third-party substitute outcomes. Aggregating across age cohorts, the results show negligible effects on any third-party outcome, with Amazon pricing slightly less than pre-entry substitute product average prices and earning revenues substantially less than pre-entry third-party averages.

Table 10 demonstrates that there is, as for within-product entry, important cohort effects and quantify the magnitudes of Amazon's effects. The first row in Table 10 shows, as for our within-product analysis in Section 3.2 above, that Amazon PL entry in competition with products that are (on average) early in their life cycle is likely associated with important unobserved demand shocks, with third-party quantities and revenues increasing and prices falling. As such, none of these should be interpreted as causal effects. Amazon PL entry into older product cohorts that fail to reject the assumption of common pre-trends show very modest effects: no impact on average third-party prices or revenues, despite Amazon charging lower prices, a positive effect on third-party quantity, and Amazon selling or earning a small fraction (1-10%) of the quantities or revenues of pre-entry third-party levels.[49]

3.4.3 Effects of Amazon entry across products: Interpretation

Considering the effects of Amazon entry across products within subcategories, the evidence suggests Amazon entry on Amazon Marketplace causes market expansion rather than business stealing. Considering a more targeted analysis of Amazon Private Label entry, for those product cohorts for which a causal analysis is most supportable (with product ages of 50 or more weeks), there is no evidence of significant price, revenue, or quantity effects on third-party merchants and Amazon, when it enters, charges lower prices and earns a small fraction of pre-entry third-party substitutes' revenue or quantity. Taken together, the interpretation of the effects of Amazon entry across products in Germany's Home & Kitchen is comparable to that for our within-product effects analysis: we find no evidence of the expropriation of significant third-party sales, or indeed any material third-party harm.

4 Predictors of Amazon Entry

4.1 Context and testable implications of the existing literature

In our final section, we now to examining the factors that *predict* which products Amazon chooses to offer. We do so, however, only for Amazon entry decisions *within existing products*, for the dual reasons that this business practice is one of the two pillars of policy concerns regarding Amazon behavior and that they are the most straightforward to address from an empirical perspective.[50] As discussed in Section 3.1, our analysis

[49]Statistical tests for common pre-trends between the treated and control groups are rejected for all outcome variables in the youngest cohort and for revenues and quantities in the oldest cohort, with a positive pre-trend in treated markets.

[50]We don't, by contrast, seek to model Amazon's decision to enter with particular Private Label products for the same reasons (and more) that complicated the measurement of Private Label effects: we would need to know which non-Private Label products are likely substitutes of the Private Label product, not only for those Private Labels that they chose to introduce, but also those that they could have but didn't. The latter is particularly difficult given the size and scope of Amazon Marketplace, and therefore

of within-product entry focuses on cases when there is a single third-party merchant selling the product in its first four weeks of life ("single-merchant entry"); subsequent entry by Amazon in such products accounts for slightly more than 20% of its Marketplace revenue in the Home & Kitchen department in Germany in our sample period.

The possibilities for analyzing Amazon entry within existing products are promising. There are many thousands of entry events and we have the ability to measure many (but not all) of the factors that could influence Amazon's entry decisions. Furthermore, some of these factors are known only to Amazon by virtue of its ownership of Marketplace (e.g. existing products' revenue or revenue growth), whereas others are observable to third parties (e.g. sales ranks, number of competitors), enabling us to assess the potential relevance of Amazon having access to aggregated Marketplace data to inform its entry decisions.

We provide two important caveats about this claim, however. First, since 2014, Amazon has had a Seller Data Protection Policy that "prohibits Amazon Retail teams from using non-public seller-specific data to compete against third-party sellers."[51] In what follows, we will only use aggregate (product-level) information, thus (we believe) satisfying the requirements of the Seller Data Protection Policy.[52] Second, and more important, we do not have access to all possible determinants of Amazon entry decisions (e.g. external competitor information, internal profit information, and other potentially important factors). As such, it is very possible that covariates that we include in our analysis not only measure the causal effect of that variable on Amazon's entry decision, but also pick up the effects of other factors we are not able to measure that are correlated with it. We do not, therefore, consider this a causal analysis; instead we interpret our results as *predictive* and assess whether the signs and magnitudes of coefficients are broadly consistent with the economic forces identified in the economic literature as relevant to Amazon's entry decisions.

What are these forces? The literature analyzing economic entry in general emphasizes, quite naturally, that firms prefer to enter markets where demand is high (and/or growing), costs are low (and/or falling), and competition is low (Berry and Reiss 2007). The economic literature analyzing hybrid marketplaces provides further predictions based on the vertical relationship between the marketplace as marketplace provider and as one more retailer on the marketplace. Nosko and Tadelis (2015), using eBay data, show that decentralized

beyond the scope of this paper. We also are not able to estimate the factors that influence Amazon "de novo" entry (or analyze cross-product effects more generally), as again many of the key factors that would enter this decision (the set of possible products not currently offered on Marketplace, the extent of any difference in the set of products offered on Marketplace relative to rival online platforms, and others) are not in our data.

[51]Despite this policy, there have been many claims that it has not been uniformly monitored and enforced, at least in the US and India (House Judiciary Committee's Antitrust Subcommittee (2020, pp 274-282), Kalra and Stecklow (2021)). We are not aware of any violations of this policy in Amazon's Germany Marketplace that we study.

[52]Technically, our approach of aggregating information to the level of the product provides merchant-level information when there is only a single merchant selling a product prior to Amazon entry (and/or Big 3P entry in such specifications). However, this arises in only 6-8% of products (weighted by revenue), so for practical purposes our regressions are relying on the same kind of aggregated data on which Amazon's policies permit itself to rely.

sellers do not internalize the impact of their actions on the marketplace as a whole, inducing a reputational externality across sellers (i.e. buyers tend to blame the platform, not a bad seller, for a bad outcome on the platform). Their mitigation strategy for the platform is to promote high-quality sellers in search results; the analogous outcome in our setting would be for Amazon to enter into markets where there are low-quality sellers. Etro (2021b) analyzes Amazon's entry incentives and finds, under a range of demand conditions, that they are aligned with consumer welfare: entry reduces prices, increasing consumer conversion rates, and proportionately benefiting both the platform and consumers. It further shows that, because Amazon can monetize third-party sales via commissions, it has no reason to foreclose third-party rivals, instead having an incentive to enter only when it has a competitive advantage from doing so (e.g. when it can exploit its efficient logistics operations) or when there is third-party-merchant market power (e.g. via Private Label entry), factors which increase the value of the marketplace not only for consumers, but also for third-party sellers.

Not to say there are not tradeoffs. Anderson and Bedre-Defolie (2021) endogenize the fees platforms charge sellers and find that the hybrid mode for a monopolist platform encourages higher fees (due to standard margin-squeeze arguments), thus lower variety and consumer welfare. Hagiu et al. (2020) examine the policy effects of banning hybrid marketplaces, finding this would be consumer and total welfare-reducing. Policies that limit the imitation of highly innovative products and prevent steering of buyers to the hybrid's own products would be preferred. Madsen and Vellodi (2021) analyze the exploitation of data by a hybrid platform and find its optimal policy must trade of the ex post benefits of successfully imitating successful products against the ex ante reduction in innovation caused by such imitation. In this paper, we look at a single Marketplace department with a fixed commission fee and thus cannot test the implications of these theories on marketplace fees, focusing instead on whether the predictors of Amazon entry decisions are more consistent with factors that internalize potential negative externalities, enhancing the value of Marketplace for consumers and firms, or more consistent with exploitation of high-demand/high-growth products brought to marketplace by third-party sellers, possibly using Marketplace data not available to rival entrants.

4.2 Empirical model and results

4.2.1 Empirical Model

To do so, we consider two versions of the question, "which products on Marketplace does Amazon enter?" First, we ask it unconditionally, analyzing Amazon's entry decisions across the Home & Kitchen department where a product exists and has been sold by a third-party merchant for a minimum of four weeks.[53] For convenience, we ignore questions of *when* Amazon enters in favor of what predicts Amazon entry, *whenever* it occurs. Thus our analysis is cross-sectional: an observation is a product, i, and $AmEntry_i = 1$ if Amazon entered into this product (after its fifth week of life) at some point during our sample period. $AmEntry_i = 0$ before its entry date (where it entered) and for all other marketplace products in which Amazon chose not to enter during our sample period.

We also seek to benchmark Amazon's entry decisions against other retailers most similar to it. We determined that the closest likely comparable retailers are "big" third-party merchants, i.e. the top 100 such merchants that have the highest in-sample Home & Kitchen revenue. As described earlier, these big merchants, while less than 1% of all Marketplace merchants, earn a third of third-party revenue on Marketplace. We therefore ask the related question, "which products on Marketplace does Amazon enter *first*?", i.e. *before* a big third-party retailer. As highlighted in the theoretical literature summarized above, to the extent Amazon's entry decisions are driven, at least in part, to maximize the value of the marketplace as a whole, they are likely to be driven by factors different from those of large 3P merchants, who seek only to maximize their own profits. In this specification, an observation is again a product, i, $AmFirst_i = 1$ if Amazon entered into this product before a big third-party merchant, and $AmFirst_i = 0$ if a big third-party merchant was the first to enter the product. Naturally the estimates from such a specification measure only the *difference* in impact each predictor has on Amazon versus third-party incentives to enter a product.

The regression equations for both of these specifications are simple Linear Probability Models with a (near-) common set of covariates:

$$y_i = DemandFactors_i'\beta_{Dem} + Comp\&PlatFactors_i'\beta_{Comp} + PlatAttractiveness_i'\beta_{Platform} + \epsilon_i \quad (8)$$

where y_i is either $AmEntry_i$ or $AmFirst_i$, according to the two specifications described above, $DemandFactors_i$, are covariates we expect potential entrants to be aware of that measure the expected demand and/or demand growth for product i, $Comp\&PlatFactors_i$ are covariates likely to measure the expected competitiveness of product i (that could also be important from the Platform's perspective), and $PlatAttractiveness_i$ are covariates likely to be measure features important to the attractiveness of the platform that might be more salient to Amazon's entry decisions than to a third-party merchant's. Note that these designations are merely suggestive and their interpretations are not causal. Individual covariates can proxy for multiple potential influences (e.g. competitiveness and platform considerations); this will be evident in the empirical results to

[53]The restriction that Amazon not enter in the first four weeks is also what we did in the effects section above and speaks to the desire to address the policy questions about expropriation of third-party sellers' information and data.

come. All covariates are averaged across time: for the 10 weeks before Amazon or big-third-party-merchant entry (as the case may be), and across the full sample for products where Amazon never entered.

We consider a range of demand factors. These include the log of (1 +) the pre-entry (total third-party) revenue of the product, the inverse of the sales rank of the product in its subcategory (thus higher values indicate more attractive sales positions), and, in some specifications, measures of revenue growth.

In both the text and the tables, we distinguish between covariates that are likely to be observed only by Amazon versus those that are also observable to third-party merchants (a topic we discuss in more depth in the next subsection). Among the demand factors, $Log(1 + Revenue)$ and a product's *High/Low/No growth* status rely on internal product-level sales data observed by Amazon but not by a third-party merchant; in the tables these are written in italicized script. By contrast, the inverse sales rank is our approximation to similar information provided to all third-party merchants by Amazon in their Seller Central Marketplace services, and is therefore not italicized.

We consider as well a range of factors that measure the current (and thus expected) competitiveness of product i. These include the number of active merchants (as we've defined them in this project),[54] the number of merchants offering the product (regardless of sales), whether or not a third-party merchant is offering the product Fulfilled by Amazon (FBA), and whether or not there is a big third-party merchant already selling the product. The number of offering merchants and whether there is an FBA or big third-party merchant is clearly observable to other third-party merchants. While we created the number of active merchants using sales data only available to Amazon, whether third-party merchants could approximate it is not so clear.[55] To be conservative, while "partially observable," we include the number of active merchants in the tables in italicized text.

We call these covariates competitive/platform factors as, all else equal, increases in the number of efficient merchants selling a product will tend to make the product less profitable for any potential entrant, but it will also be perceived to be "well served" from the platform's perspective as it is more likely that there are already efficient sellers in place to sell the product. Both suggest negative effects on Amazon's entry decisions.

Our final set of covariates focuses on considerations that are particularly salient to the attractiveness of the marketplace beyond the individual product. These are average product availability and whether or not a product is on offer but has not yet made any sales. Lack of product availability and the listing of a product with terms and conditions sufficiently unattractive to fail to result in any sales are both potentially factors

[54]The number of merchants that contributed to the first 90% of the sales of that product.

[55]Third-party merchants monitoring a product market could likely determine the number and identity of active sellers by carefully monitoring the terms of their offers to consumers, including whether/not any (and how many) win the Buy Box.

for any firm to enter to provide a better price/availability, but they are likely to induce a significant negative consumer experiences from a platform perspective, further increasing Amazon's incentives to address them via product entry. Both such covariates would be observable only to Amazon using Marketplace data.

4.2.2 The Role of Sellers' Data in our Analysis

As described in the Introduction, many of the concerns about Amazon's Marketplace entry decisions relate to its potential use of third-party seller Marketplace data to inform its entry decisions. These discussions sometimes conflate *seller-specific data* with *aggregate data*, i.e. data aggregated across multiple sellers but still only available to Amazon. As described in Section 4.1 above, Amazon has since 2014 had a Seller Data Protection Policy of not using non-public, seller-specific data, albeit there are concerns that this policy has not been uniformly monitored and enforced. Such data is distinct from data aggregated across sellers, for whom such a policy does not apply.

As described in Section 4.1 above, our empirical model constructs predictors of Amazon's (and Big 3P merchants') product-level entry decisions using pre-entry Marketplace data at the level of *individual products*. But for the few cases where there is a single merchant selling a product for all weeks prior to Amazon (or Big 3P) entry (6-8% when weighted by revenue), our analysis relies exclusively on the type of aggregated data permitted under Amazon's Seller Data Protection Policy. As such, it cannot speak directly to the differential effects of using aggregate versus seller-specific data.

What our analysis can do, however, is speak to the predictive value of "public" information likely to be observed by both Amazon and other 3P merchants alike versus "non-public" information likely to be observed only to Amazon by virtue of its ownership of Marketplace. Of the covariates described in Section 4.2.1 above, we argued that four are likely to be public/observable-to-third-party-sellers measures of demand or competitive conditions (a product's inverse sales rank, the number of offering merchants, and whether or not there is an FBA or Big merchant present) and the remaining seven are likely to be to be non-public/unobservable measures of demand, competitive conditions, and platform externality factors (pre-entry product revenue and revenue growth, the number of active merchants, and measures of product/existing seller quality like availability and the presence of offers without sales). One goal of the empirical analysis is to determine the extent to which non-public information available to Amazon by virtue of owning Marketplace can predict Amazon's entry decisions relative to public information, and to what extent the patterns of such predictions are consistent with exploitation of third-party sellers versus internalizing Marketplace externalities. The next sections describes our results and their interpretation along these lines.

4.2.3 Results

Table 11 presents the results predicting Amazon entry, both relative to those products it chose not to enter and relative to those products where it entered before a big third-party seller, with the final set of columns reporting the difference in coefficients across the two dependent variables. To foster comparability with later results that were not able to calculate the demand growth variables, we present baseline results both including and excluding them.

The first two columns of Table 11 measure the correlates that predict Amazon entry into a pre-existing Marketplace product. They show that Amazon entry depends in mixed ways on demand levels (anyway with small magnitudes), but is strongly associated with high demand growth.[56] It is less common the more offering and active merchants are present, but (contrary to expectation) increasing in the presence of a big or FBA merchant. These latter could be proxying for unobserved (by us) demand shocks correlated with the entry of such merchants. As expected, Amazon is more likely to enter the lower is existing product availability and when there are products on Marketplace where existing seller offers are not attractive enough to yield sales (e.g. due to high prices, lack of availability, or other factors).

The next two columns of Table 11 measure the *relative* importance of the same covariates for determining whether Amazon or a big third-party merchant enters an existing product first. (For expositional convenience the third pair of columns reports the difference in the estimates across the first two pairs of columns). The results show that Amazon is *less* responsive to demand factors in their entry decisions (or in the speed of their entry decisions) than are big third-party merchants. For example, a product moving from the lowest to highest possible sales rank (0 to 1) is associated with a thirteen percentage point smaller predicted first-to-enter probability for Amazon relative to a big third-party merchant. By contrast, Amazon is more responsive to the presence of existing merchants (being more reluctant to enter relative to a big third-party merchant), with the converse the case for the presence of an FBA merchant (with big third-party merchants being now much more reluctant to enter). Amazon is also more responsive than big third-party merchants with respect to lack of product availability, albeit (surprisingly) less responsive to products with offers but no sales.[57]

As our effects analysis in Section 3.2 showed heterogeneous effects associated with the age of a product at the time of Amazon's entry, Table 12 explores whether similar heterogeneity is present in our analysis of

[56] To foster interpretability, note that these results say that a high-growth product is associated with a 52 percentage point higher Amazon entry probability, whereas a product moving from 2nd (1/2=0.5) to 1st (1/1=1) in its subcategory sales rank is associated with a 1 percentage point lower Amazon entry probability.

[57] We interpret variables observable to Amazon but not third-party merchants as if third-party merchants did not consider such a variable in their decision-making but Amazon did (or could). If third-party merchants made random decisions related to products with offers and not sales, these results would suggest Amazon would be even less likely to enter relative to this benchmark. That seems unlikely, suggesting the covariate is picking up some other unmeasured factors that differentially affect Amazon and third-party entry decisions.

the predictors of Amazon's entry.[58] In fact there is surprising homogeneity, with the strongest differences across cohorts showing that Amazon is much more unresponsive to products' sales ranks than are third-party merchants in all but first-to-enter into the oldest cohort (with the coefficient magnitude 4 times the across-cohort estimate for entry into products 25-49 weeks old).

4.3 Predictors: Interpretation

The goal of our empirical analysis in this section is twofold. First, we wish to measure the predictors of Amazon's entry decisions to assess their potential motivations: are their entry patterns consistent with exploiting third-party merchants or with internalizing marketplace externalities (or perhaps both)? Second, what role does aggregate (across sellers) data which is only available to Amazon appear to predict their entry decisions relative to those of third-party merchants who do not observe such data.

The results predicting Amazon entry in isolation (the first two columns of Table 11) presents evidence more in favor of internalizing externalities than exploiting third-party merchants: its entry is correlated with high-growth, low-competition markets, even if there are other big and/or efficient (FBA) sellers present. While this may harm pre-existing sellers, such is the nature of a competitive markets in general and the results of section 3.4 above suggest that Amazon entry cannibalizes little aggregate third-party revenue. Furthermore, Amazon entry is particularly likely when there are third-party offers but no sales (suggesting low-quality or capacity-constrained product listings) and when product availability is low.

The picture is even more consistent with the goal internalizing marketplace externalities when Amazon's entry decisions are benchmarked against those of big third-party merchants. The results show that Amazon enters product markets before third-party merchants when demand is low, concentration is high, and product availability is low.[59] Furthermore, predictors in italicized font that are observed by Amazon but not by third-party merchants (demand, demand growth, low competition, and availability) are strongly associated with internalizing platform externalities associated with insufficient variety (as proxied by low-demand goods), competition within a product, and reputational concerns associated with product stock-outs. Such an entry strategy is more consistent with one which makes Marketplace more attractive to consumers (and, by extension, third-party merchants) than one which seeks to expropriate third-party seller sales.

[58] We were not able to measure the demand growth variables for the two youngest entry cohorts, and so drop these variables from the analysis and compare results across cohorts and for the pooled regression for this specification.

[59] The only puzzle is Amazon's high entry propensity into products where there already exists an FBA merchant. If this coefficient indeed reveals a causal effect and not a spurious correlation, it could signal a market for which Amazon's efficiency advantages beyond fulfillment may be beneficial (e.g. low-value "staples"), or that Amazon's entry costs are lower due to greater information about that product's fulfillment cost requirements. Further investigation of these considerations would be welcome.

5 Conclusion: Policy implications of our findings, limitations, and directions for future research

The goal of this paper has been to address the policy issues raised in the public debate regarding Amazon's Marketplace business practices related to product entry. There are broadly three main concerns: first, that Amazon misappropriates third-party seller value on Marketplace by entering with products in competition with merchants' most successful products; second, that it uses Marketplace data to enable such a strategy; and third, that third-party merchants and consumers are harmed by such strategies, the former directly and the latter via reduced innovation on the platform.

We've sought to evaluate each of these concerns by examining the predictors and effects of Amazon's entry decisions in the Home & Kitchen department on the Germany Marketplace between July 12, 2016 and May 31, 2021. In Section 4, we assess the first two of these concerns for Amazon entry into products that were introduced to marketplace by third-party sellers. Our results provide much stronger evidence for internalizing platform externalities (to the benefits of consumers and third-party merchants alike) than expropriation of third-party seller sales: while Amazon tends to enter high-growth, low-competition markets, *relative to other big third-party merchants*, they appear to enter first low-growth, (even-)lower competition, low-product availability markets. We were not able to address the question of whether or not Amazon uses seller-specific Marketplace data to inform their entry decisions; to the extent they use aggregated (across sellers) Marketplace data, it appears they do so to create a more attractive platform for consumers than to exploit successful (i.e. high-demand) third-party products.

In Section 3, we assess the third concern regarding consumer and merchant effects. Our efforts were complicated by the revelation of complicated life-cycle effects for which we could only imperfectly control. Focusing first on the effects of Amazon entry into existing products, and excluding such entry into early age cohorts, where such life-cycle considerations were strongest, we found that Amazon entry was correlated with slight price reductions and, surprisingly, lower third-party availability. For third-party merchants, we found little, if any, displacement of third-party revenue in the first 40 weeks after Amazon entry, and that Amazon itself sold only between 3-7% of pre-existing third-party quantity or revenue. Amazon often entered and frequently failed (40% of the time) and its entry was associated with net exit only in the latest entry cohort, with small magnitude (0.07 fewer active sellers). These effects are all modest and more consistent with mild market expansion than business stealing. We also investigated the impact of Amazon entry on merchants' subsequent innovation, benchmarking the effects against those of Big 3P sellers, but the results likely capture regression to the mean in new product introductions than the causal effects of either Amazon or Big 3P entry.

We also examined cross-product effects, albeit in a more limited way due to the challenge identifying sets of products likely to be affected by Amazon entry as well as other products which could serve as an appropriate control group for the "treated" (by entry) products. We first characterized general cross-product entry cannibalization effects within Home & Kitchen subcategories, finding that Amazon entry was more consistent with market expansion than business stealing relative to entry by fringe or large third-party merchants. These are important from a policy perspective given the large share of revenue associated with *de novo* Amazon entry on Marketplace. We also examined the impact of Amazon Private Label (PL) entry. We used Amazon's historical search results and the definition of subcategories to identify, for each of the largest PL products, a set of substitute products most likely to be impacted by Amazon entry as well as a set of appropriate control products for these substitutes, finding results qualitatively similar to that for within-product entry: excluding effects on substitutes early in their life cycles, Amazon entry is associated with an increase in total quantities sold of third-party substitutes, with no estimated change in average prices or revenues, while it charges lower prices for some entry cohorts and is associated with sales between 1-10% of pre-entry third-party totals.

These conclusions come with a number of important limitations. Due to the computational demands of analyzing such a large data environment, we analyzed only the Home & Kitchen department on the Germany Marketplace between 2016-2021: it is possible that other patterns could arise in other departments or in other countries or in other times. Our analysis of Private Label products necessarily relied on important assumptions on which were both the "treated" and "control" groups of products; different definitions are possible and these could yield different results. Our analysis used methods commonly applied to reveal causal effects in a wide variety of settings, but outcomes on Amazon Marketplace reflect challenging unobserved life-cycle effects; further research would be welcome to directly address this challenge and/or explore further dimensions of heterogeneity in the estimated effects. Finally, the goal of this project has been to measure the effects of Amazon entry on Amazon Marketplace "in the round." We do not dismiss the stories of individual third-party merchants whose businesses have been displaced by Amazon entry. Our goal has been to access as large a portion of Marketplace data as possible to assess how representative might be such stories. Where we have looked, we do not see that they are.

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Table 1: Revenue shares across Germany's Marketplace departments, 2016-2021

Department	Avg Annual Net Revenue (normalized)	Net Revenue Share	May 2021 Entering Prods Net Rev Share	Number of Products Relative to Depts' Average
Home	1.000	0.119	0.911	5.11
PC	0.823	0.098	0.947	0.68
Home Improvement	0.816	0.097	0.878	1.90
Sports	0.669	0.079	0.938	2.54
Wireless	0.572	0.068	0.976	1.64
Toys	0.445	0.053	0.910	1.39
Books	0.423	0.050	0.816	2.34
Kitchen	0.380	0.045	0.886	0.58
Health & Personal Care	0.360	0.043	0.886	0.88
Electronics	0.338	0.040	0.942	0.64
Lawn and Garden	0.323	0.038	0.894	0.77
Furniture	0.314	0.037	0.936	1.17
Office Products	0.241	0.029	0.795	0.97
Automotive	0.226	0.027	0.853	1.07
Personal Care Appliances	0.201	0.024	0.891	0.16
Camera	0.176	0.021	0.886	0.22
Pet Products	0.158	0.019	0.856	0.64
Home Entertainment	0.157	0.019	0.985	0.03
Grocery	0.138	0.016	0.871	0.53
Baby	0.137	0.016	0.901	0.36
Major Appliances	0.132	0.016	0.924	0.06
Video Games	0.128	0.015	0.977	0.08
Biss	0.113	0.013	0.914	0.36
Luggage	0.085	0.010	0.944	0.37
Jewelry	0.066	0.008	0.956	0.50
Total or Average		1.000	0.907	

Note: For 25 of the 28 largest departments by revenue on Amazon's Germany Marketplace, reported is its average annual net revenue (scaled to that of the highest-revenue department), its total Marketplace revenue share, the share of last-month Marketplace revenue earned by products that entered in our sample period, and the total number of products sold relative to the across-department average number of products.

Table 2: Revenue shares of products in Markeplace by Amazon presence and type of product

				Among All Products		Among Products Where Amazon is Present	
Is Amazon Present?	Did Amazon Enter In Sample?	Did Amazon Enter First In Sample?	Product Type	Type Revenue Share	Total Across-type Revenue Share	Type Revenue Share	Total Across-type Revenue Share
Yes	Unknown	Unknown	Incumbent	0.095	0.095	0.244	0.244
Yes	Yes	Yes	Single-merchant entry	0.136		0.349	
			Multi-merchant entry	0.054	**0.190**	0.138	**0.487**
Yes	Yes	No	Single-merchant entry	**0.079**		**0.203**	
			Multi-merchant entry/ Incumbent	0.026	0.105	0.067	0.269
No	No	n/a	Incumbent	0.032			
			Single-merchant entry	0.552			
			Multi-merchant entry	0.027	0.611		

Note: Reported is the share of revenue accruing to products on Germany's Marketplace in our sample period by whether or not Amazon is active, whether or not Amazon entered the product in our sample period, and whether or not they entered that product first (i.e. before a 3P merchant). Incumbent products are those that were present at the beginning of our data, in which case we do not know whether or not Amazon entered before or after a third-party merchant. Single-merchant entry products are those for which a single seller sold that product for the first four weeks of its life; multi-merchant entry products are those sold by multiple sellers in the first four weeks of their lives. The product revenue shares for the samples on which we conducted our within-product analysis (single-merchant entry products where Amazon was not first) and cross-product analysis (all products where Amazon was first) in Sections 3.2 and 3.4 are given in bold font.

Table 3: Treatment effects of Amazon entry within existing products: consumer outcomes

	Prices		Availability
Product Age at Entry Cohort	Third Party	Amazon	Third Party
l.t. 25 weeks	**-0.056**	**-0.063**	**0.113**
	(0.015)	(0.013)	(0.042)
25-50 weeks	-0.003	-0.008	-0.022
	(0.016)	(0.021)	(0.023)
50-100 weeks	**-0.028**	-0.005	**-0.053**
	(0.009)	(0.008)	(0.011)
100+ weeks	-0.013	**-0.028**	**-0.046**
	(0.007)	(0.010)	(0.013)
Fixed Effects:			
Product	Yes		Yes
Merchant	n/a		n/a
Week	Yes		Yes
Age	Yes		Yes

Note: Reported in columns labeled "Third Party" are estimated common-within-age-at-entry-cohort treatment effects of Amazon entry on average third-party prices and availability by product age at entry cohorts. Parameter estimates measure the effect of Amazon entry on the outcome relative to the 10-week pre-entry average of third-party sellers. Also reported in columns labeled "Amazon" are the values of post-entry Amazon prices and availability relative to the same pre-entry third-party average. Standard errors are clustered at the product and week levels. Statistically significant results at the 5% level are reported in bold.

Table 4: Treatment effects of Amazon entry within existing products: merchant outcomes

	Revenue		Quantity		Quarterly Active Merchants	
Cohort	Third Party	Amazon	Third Party	Amazon	Third Party	Amazon
l.t. 25 weeks	-0.006	1.226	-0.044	-0.102	**0.351**	**0.618**
	(0.353)	(1.133)	(0.208)	(0.432)	(0.167)	(0.036)
25-50 weeks	0.017	**-0.945**	-0.007	**-0.965**	0.135	**0.663**
	(0.206)	(0.031)	(0.193)	(0.017)	(0.111)	(0.047)
50-100 weeks	-0.157	**-0.971**	-0.117	**-0.948**	-0.001	**0.645**
	(0.153)	(0.012)	(0.086)	(0.021)	(0.049)	(0.045)
100+ weeks	-0.264	**-0.935**	-0.116	**-0.940**	**-0.071**	**0.598**
	(0.191)	(0.038)	(0.144)	(0.019)	(0.036)	(0.041)
Fixed Effects:						
Product	Yes		Yes		Yes	
Merchant	Yes		Yes		Yes	
Week	Yes		Yes		Yes	
Age	Yes		Yes		Yes	

Note: Reported in columns labeled "Third Party" are estimated common-within-age-at-entry-cohort treatment effects by product age at entry cohorts of Amazon entry on total third-party revenue and quantity, as well as on the number of quarterly active third-party merchants. Quarterly-active merchants are those merchants, ranked by sales, that contribute to 90% of a product's sales in that quarter. Treatment effect estimates are given by $(\exp(\hat{\tau}_{r,m}) - 1)$ for cohort r and merchant m (3P, Amazon) and can be interpreted as the proportionate effect of Amazon entry on the outcome relative to the 10-week pre-entry total of third-party sellers. Also reported in columns labeled "Amazon" are the values of post-entry Amazon revenue and quantity relative to the same pre-entry third-party total, as well as the probability that they continue to sell the product over 40 weeks post-entry. Standard errors are clustered at the product and week levels and treatment effect standard errors are calculated via a parametric bootstrap. Statistically significant results at the 5% level are reported in bold.

Table 5: Product and revenue shares by product growth types, Home & Kitchen department

Product Type	Share of Products	Share of Revenue
high growth	0.113	0.458
low growth	0.111	0.324
no growth	0.191	0.111
short exit	0.133	0.03
instant exit	0.289	0.005
not enough data	0.163	0.072
Top 3 groups	0.415	0.893

Note: Reported is the share of products and revenue by product growth types in the Home & Kitchen department in our sample period. Product growth types are not an Amazon construct; they are defined by the authors based on the rate of product revenue growth over products' lifetime on Marketplace (see text for details).

Table 6: New product introductions by pre-entry product growth segment

		No Previous Pre-entry High-growth New Product Introductions			One Previous Pre-entry High-growth New Product Introductions			Two+ Previous Pre-entry High-growth New Product Introductions		
		All	High Growth	Non-High Growth	All	High Growth	Non-High Growth	All	High Growth	Non-High Growth
Amazon	Pre-entry	0.184	0.070	0.114	0.339	0.124	0.215	1.432	0.679	0.753
	Post-entry	0.170	0.071	0.098	0.186	0.061	0.125	0.983	0.540	0.443
Big 3P	Pre-entry	0.319	0.117	0.203	1.141	0.362	0.779	2.716	0.620	2.096
	Post-entry	0.274	0.062	0.211	0.706	0.233	0.473	1.824	0.279	1.545
No entry		0.885	0.221	0.664	0.176	0.080	0.097	2.027	0.759	1.268
Overall		0.648	0.169	0.478	0.258	0.097	0.161	1.677	0.672	1.005

Note: Reported is the average number of weekly new product introductions by "fringe" third-party merchants (those outside the top 100) segmented by the number of previous high-growth products introduced (0, 1, 2+) in the Home & Kitchen department in our sample period. Reported are averages for those merchants that first experience Amazon entry, that first experience Big 3P entry (those inside the top 100 third-party merchants), and that experience no entry, as well as the overage average for that pre-entry product growth segment.).

Table 7: Treatment effects of Amazon and Big 3P entry on third-party merchant new product introductions

	Effects of Amazon entry			Effects of Big 3P entry		
Previous High-growth New Product Introductions	All New product Introductions	High-growth New Product Introductions	Non-High-growth New product Introductions	All New product Introductions	High-growth New product Introductions	Non-High-growth New product Introductions
None	0.153	0.066	0.087	-0.071	-0.023	-0.048
	(0.097)	(0.045)	(0.054)	(0.166)	(0.060)	(0.119)
One	-0.059	-0.041	-0.018	**-0.964**	**-0.204**	**-0.760**
	(0.152)	(0.058)	(0.101)	(0.417)	(0.091)	(0.337)
Two or more	**-0.638**	**-0.268**	-0.370	-1.199	-0.377	-0.822
	(0.303)	(0.127)	(0.189)	(0.837)	(0.296)	(0.677)
Fixed Effects:						
Product	n/a	n/a	n/a	n/a	n/a	n/a
Merchant	Yes	Yes	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes	Yes	Yes
Merchant Age	Yes	Yes	Yes	Yes	Yes	Yes

Note: Reported are the estimated treatment effects of the first entrant, Amazon or a Big 3P merchant, on a Fringe merchant's subsequent introduction of new products, with effects estimated separately for cohorts based on previous number of new product introductions. Big 3P and Fringe merchants are those inside/outside the top 100 in sales in the Home & Kitchen department. Estimated magnitudes may be compared with pre-entry average new product introduction rates reported in Table 6 above. Standard errors are clustered at the merchant and week levels. Statistically significant results at the 5% level are reported in bold.

Table 8: Top 10 subcategories in the Home & Kitchen department

Rank	Subcategory	“Active” Products	“Active” Entry Events
1	Robotic Vacuums	84	163
2	Espresso Fully Automatic	81	65
3	Stick Vacuum Cleaners	125	221
4	Deep Fryers	127	169
5	Hot Beverage Makers Accessories	393	922
6	Cylinder Vacuum with Dust Bag	82	105
7	Blenders	289	458
8	Indoor Grills	92	167
9	Cleaning Tools & Supplies	317	455
10	Cylinder Vacuum Bagless	51	88

Note: Reported are the 10 largest subcategories by revenue in the Home & Kitchen department, the number of “active” products (those that, when ranked by revenue, contribute to 90% of that subcategories revenue), and the number of “active” entry events, defined as entry into an active product by an ever-active merchant (those that, when ranked by revenue, contribute to 90% of that product’s revenue in at least one quarter of its life).

Table 9: Cross-product effects of Amazon, Big 3P, and Fringe 3P entry

	Log(Total Revenue)				Log(Incumbent Revenue)			
	Fringe 3rd Party Revenue	Big 3rd Party Revenue	Amazon Revenue	Total Revenue	Fringe 3rd Party Revenue	Big 3rd Party Revenue	Amazon Revenue	Total Revenue
log(1+Fringe 3P Entries)	**0.23**	**-0.18**	**-0.14**	**0.08**	**-0.15**	-0.04	0.01	**-0.15**
	(0.019)	(0.022)	(0.019)	(0.013)	(0.027)	(0.025)	(0.019)	(0.025)
log(1+Big 3P Entries)	**-0.12**	**0.47**	**-0.13**	0.01	**0.10**	**-0.40**	-0.05	0.02
	(0.025)	(0.051)	(0.034)	(0.017)	(0.032)	(0.049)	(0.034)	(0.033)
log(1+Amazon Entries)	**-0.27**	-0.04	**0.77**	**-0.05**	0.03	**0.13**	-0.01	0.07
	(0.031)	(0.032)	(0.043)	(0.017)	(0.039)	(0.038)	(0.049)	(0.037)
log(total products)	**1.57**	**0.90**	**0.89**	**1.42**				
	(0.035)	(0.054)	(0.043)	(0.025)				
Fixed Effects:								
Subcategory	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Reported are the parameter estimates from seemingly unrelated regressions of two measures of log (1+) revenue on the number of instances of entry within each of the subcategories in the Home & Kitchen department. Each of these measures varies across three merchant types: Amazon, Big 3P merchants (those in the top 100), and Fringe 3P merchants. Also reported are regression results of total (across merchant types) revenue on the same entry measures. Standard errors are not clustered. Statistically significant results at the 5% level are reported in bold.

Table 10: Treatment effects of Amazon Private Label entry

	Prices		Revenue		Quantity	
Cohort	Third Party	Amazon	Third Party	Amazon	Third Party	Amazon
5-50 weeks	**-0.073**	-0.021	**0.606**	**-0.960**	0.533	**-0.948**
	(0.030)	(0.054)	(0.270)	(0.014)	(0.274)	(0.020)
50-100 weeks	0.009	**-0.119**	0.370	**-0.949**	**0.384**	**-0.902**
	(0.014)	(0.030)	(0.236)	(0.019)	(0.177)	(0.038)
100+ weeks	-0.020	-0.032	0.273	**-0.991**	**0.264**	**-0.986**
	(0.021)	(0.023)	(0.220)	(0.004)	(0.111)	(0.002)
Fixed Effects:						
Product	Yes		Yes		Yes	
Merchant	Implicitly w/ τ_{Am}		Implicitly w/ τ_{Am}		Implicitly w/ τ_{Am}	
Week	Yes		Yes		Yes	
Age	Yes		Yes		Yes	

Note: Reported in columns labeled "Third Party" are estimated common-within-age-at-entry-cohort treatment effects of Amazon PL entry on average third-party related products' prices and total third-party related products' revenue and quantity by product age at entry cohorts. Parameter estimates measure the effect of Amazon entry on the outcome relative to the 10-week pre-entry average of third-party sellers. Also reported in columns labeled "Amazon" are the values of post-entry Amazon prices, revenue, and quantity relative to the same pre-entry third-party average (for prices) or totals (for revenue and quantity). Standard errors are clustered at the "market" (i.e. group consisting of each PL product and its substitute products) and week levels. Statistically significant results at the 5% level are reported in bold.

Table 11: Predictors of Amazon entry

	Amazon or Not?		Amazon or Big Third Party First?		Difference	
	(A)		(B)		(B) - (A)	
	Baseline	Including Demand Growth	Baseline	Including Demand Growth	Baseline	Including Demand Growth
Demand factors						
Log (1+Revenue)	**0.01**	**0.01**	0.00	0.00	-0.01	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)		
Inverse Sales Rank	**-0.02**	**-0.02**	**-0.13**	**-0.13**	-0.12	-0.11
	(0.00)	(0.00)	(0.01)	(0.01)		
High growth product		**0.52**		**-0.14**		-0.66
		(0.00)		(0.00)		
Low growth product		**0.29**		**-0.09**		-0.38
		(0.00)		(0.00)		
No growth product		**0.02**		**-0.04**		-0.06
		(0.00)		-(0.01)		
Competitive/Platform Factors						
# Active Merchants	**-0.01**	**-0.05**	**-0.23**	**-0.21**	-0.22	-0.16
	(0.00)	(0.00)	(0.00)	(0.00)		
# Offering Merchants	**-0.01**	**-0.01**	**0.00**	**0.00**	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)		
FBA Merchant Present	**0.18**	**0.16**	**0.56**	**0.56**	0.38	0.40
	(0.00)	(0.00)	(0.00)	(0.00)		
Big Merchant Present	**0.08**	**0.08**				
	(0.00)	(0.00)				
Platform Externality Factors						
Average product availability	**-0.04**	**-0.07**	**-0.18**	**-0.17**	-0.14	-0.11
	(0.00)	(0.00)	(0.00)	(0.00)		
Product w/ Offers but no Sales	**0.77**	**0.77**	**-0.31**	**-0.33**	-1.08	-1.10
	(0.00)	(0.00)	-(0.01)	-(0.01)		

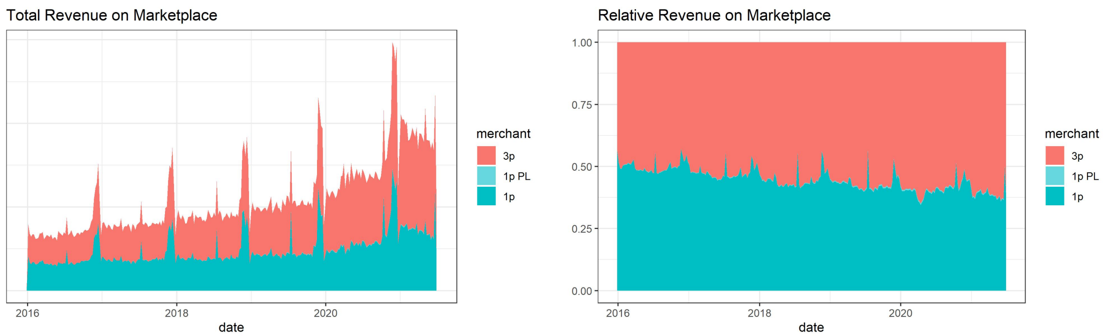
Note: Reported are the estimated predictors of Amazon entry, either unconditionally ("Amazon or Not?") or relative to Big 3P merchant entry ("Amazon or Big 3P First?"). Also reported is the difference in the results across columns. Covariates written in italics are likely to be observed only by Amazon by virtue of their access to Marketplace data; covariates without italics are likely to be observed by both Amazon and third-party merchants (see text for details). Standard errors are not clustered. Statistically significant results at the 5% level are reported in bold.

Table 12: Predictors of Amazon entry by age at entry cohort

	Amazon or Not?					Amazon or Big Third Party First?				
	Pooled	Entry Cohort 5-24	Entry Cohort 25-49	Entry Cohort 50-99	Entry Cohort 100+	Pooled	Entry Cohort 5-24	Entry Cohort 25-49	Entry Cohort 50-99	Entry Cohort 100+
	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Demand										
Log (Rev)	**0.01**	**0.01**	**0.00**	**0.00**	**-0.01**	0.00	**0.01**	**0.00**	**-0.02**	**-0.02**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Inverse Sales Rank	**-0.02**	**-0.04**	**0.00**	**-0.01**	**0.06**	**-0.13**	**-0.33**	**-0.50**	**-0.35**	**-0.13**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
High growth										
Low growth										
No growth										
Competitive										
Active Ms	**-0.01**	**-0.12**	**-0.04**	**-0.01**	**0.03**	**-0.23**	**-0.37**	**-0.31**	**-0.21**	**-0.29**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Offering Ms	**-0.01**	**-0.01**	**0.00**	**-0.01**	**0.00**	**0.00**	**0.01**	**0.01**	**0.02**	**0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FBA M	**0.18**	**0.12**	**0.09**	**0.09**	**0.08**	**0.56**	**0.69**	**0.75**	**0.73**	**0.73**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Big M	**0.08**	**0.04**	**0.03**	**0.03**	**0.05**					
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
Platform										
Avail	**-0.04**	**-0.09**	**-0.07**	**-0.06**	**-0.08**	**-0.18**	**-0.15**	**-0.12**	**-0.13**	**-0.14**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Offs no Sales	**0.77**	**0.79**	**0.84**	**0.84**	**0.83**	**-0.31**	**-0.21**	**-0.19**	**-0.25**	**-0.21**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	-(0.01)	-(0.01)	-(0.01)	-(0.01)	-(0.01)

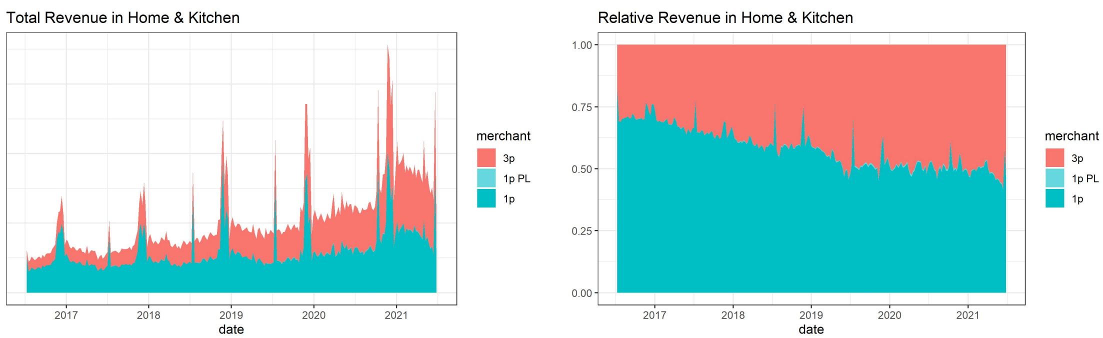
Note: Reported are the estimated predictors of Amazon entry, either unconditionally ("Amazon or Not?") or relative to Big 3P merchant entry ("Amazon or Big 3P First?") by age at entry cohort. Statistically significant results at the 5% level are reported in bold.

Figure 1: Germany Marketplace Revenue By Week and Merchant Type



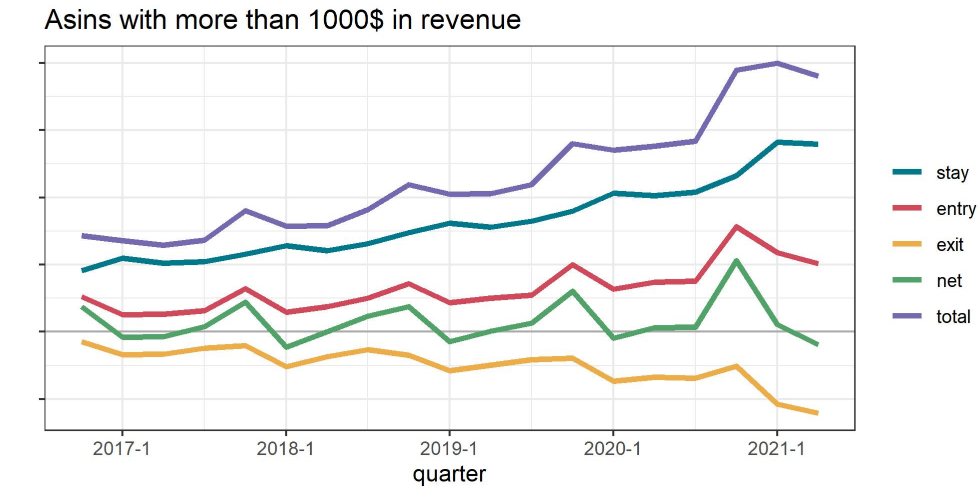
Note: Reported are the total revenue and revenue share by merchant type on Germany's Marketplace from July 12, 2016 to May 31, 2021. Units in the left panel are omitted for reasons of confidentiality.

Figure 2: Germany Home & Kitchen department Revenue By Week and Merchant Type



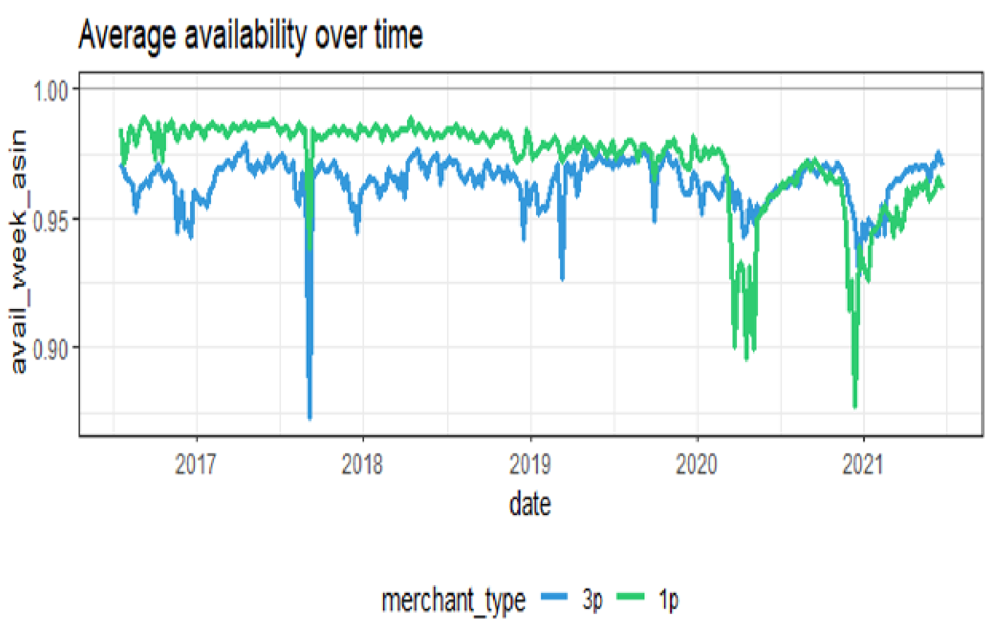
Note: These figures display the total revenue and revenue share by merchant type in the Home & Kitchen department from July 12, 2016 to May 31, 2021. Units in the left panel are omitted for reasons of confidentiality.

Figure 3: Number of Products, Home & Kitchen department



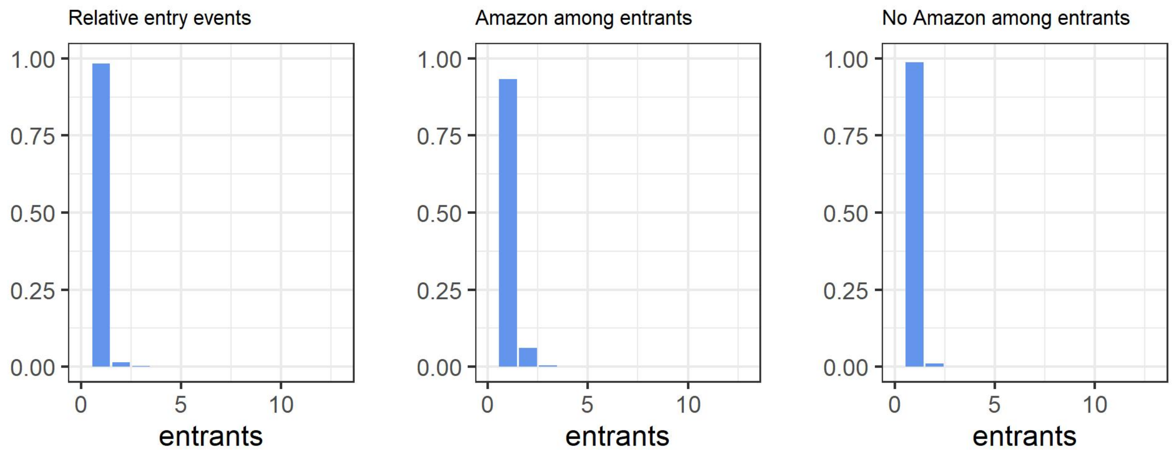
Note: Reported are the number of products offered by week in the Home & Kitchen department in our sample period, including measures of entry, exit, and net entry. Units on the y-axis are omitted for reasons of confidentiality.

Figure 4: Average Product Availability, Home & Kitchen department



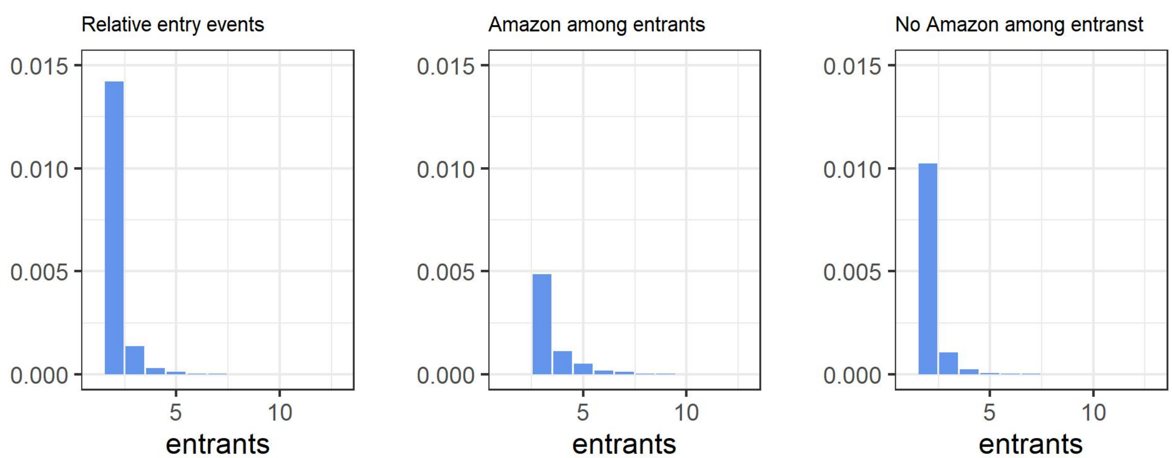
Note: Reported are the average availabilities of products offered by Amazon (1p) and third-party merchants (3p) in the Home & Kitchen department in our sample period.

Figure 5: Number of merchants upon new product entry, Home & Kitchen department



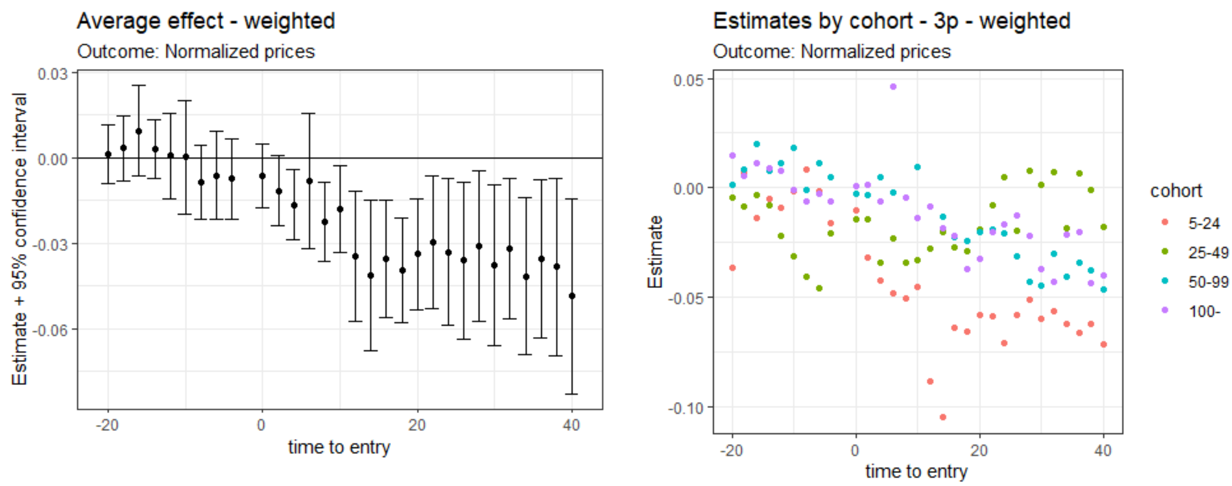
Note: Reported are the distributions of the number of merchants that enter within four weeks of the first sale of a new product in the Home & Kitchen department in our sample period. The vast majority of the time there is one such entrant; the next figure analyzes more closely when there are two or more such entrants.

Figure 6: Number of merchants upon new product entry, multi-merchant new products,



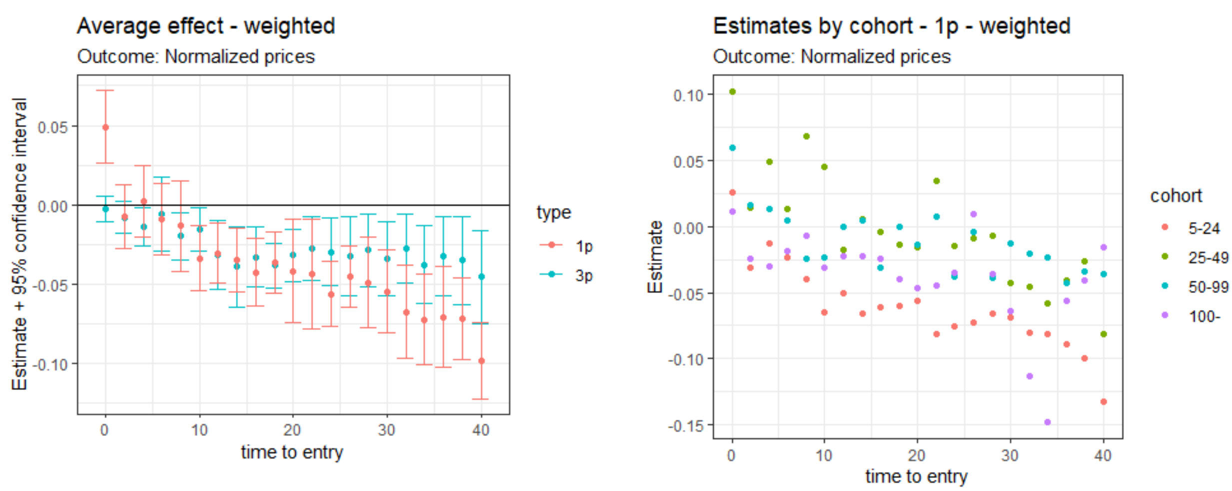
Note: Reported are the distributions of the number of merchants that enter within four weeks of the first sale of a new product in the Home & Kitchen department in our sample period, conditional on their being at least 2 such merchants in the first four weeks.

Figure 7: Price effects: Third-party, in aggregate and by age cohort



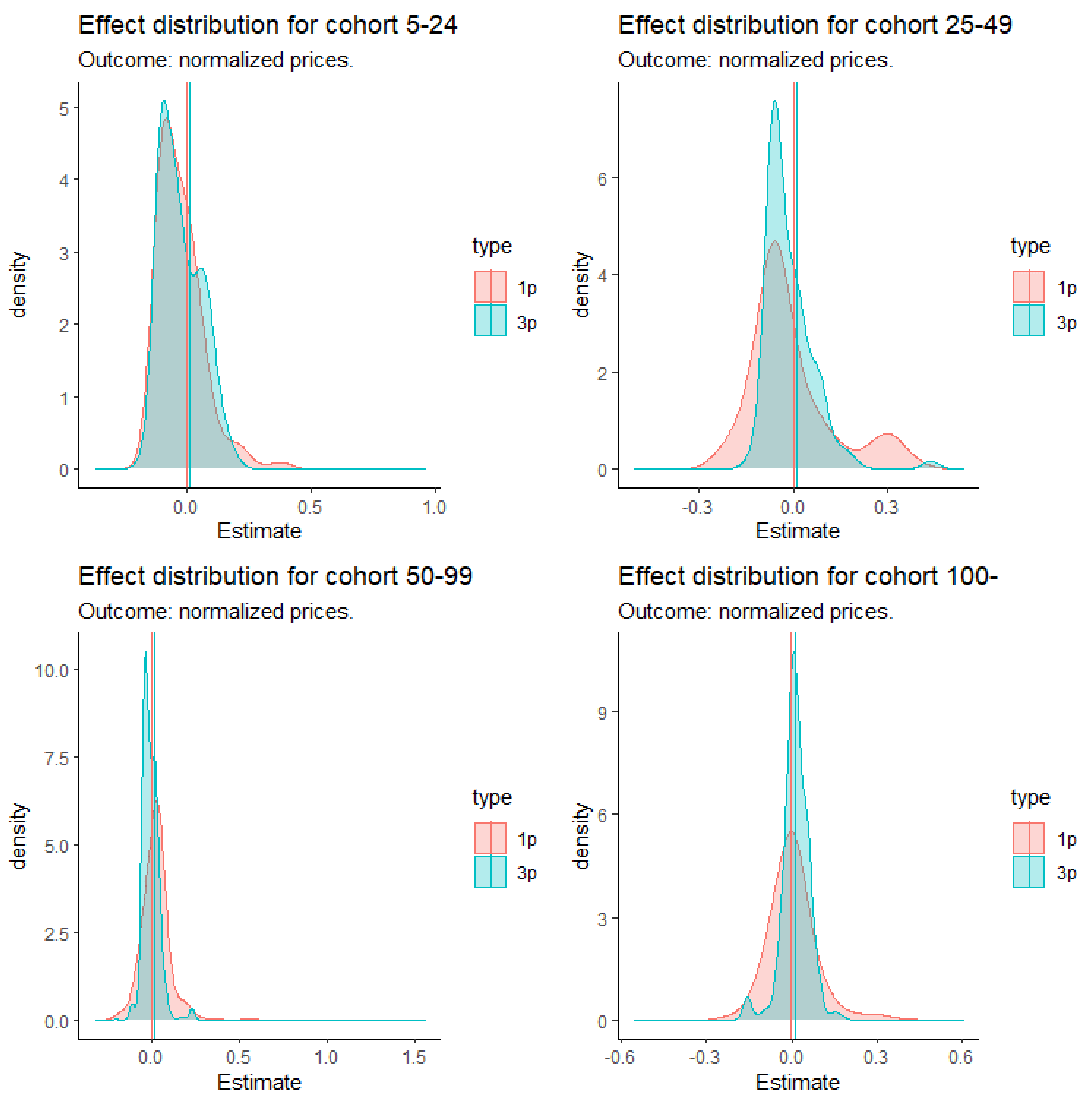
Note: Reported in the left panel are the average (across product age at entry) treatment effects of Amazon entry on average third-party normalized prices, $\hat{\tau}^{parallel}_{s,3P}$ and $\hat{\tau}_{s,3P}$, for two-week treatment windows between 20 weeks pre-Amazon entry and 40 weeks post-Amazon entry. Treatment effects can be interpreted as the estimated percentage change in average third-party prices relative to their pre-Amazon-entry average. Reported in the right panel are comparable average across-cohort treatment effects by groups of cohort weeks (with Amazon entry in 5-24, 25-49, 50-99, and 100+ weeks since a product's birth). Confidence intervals in the right panel are suppressed to foster comparability across cohorts.

Figure 8: Price effects: 3P, Amazon, and Amazon by cohort



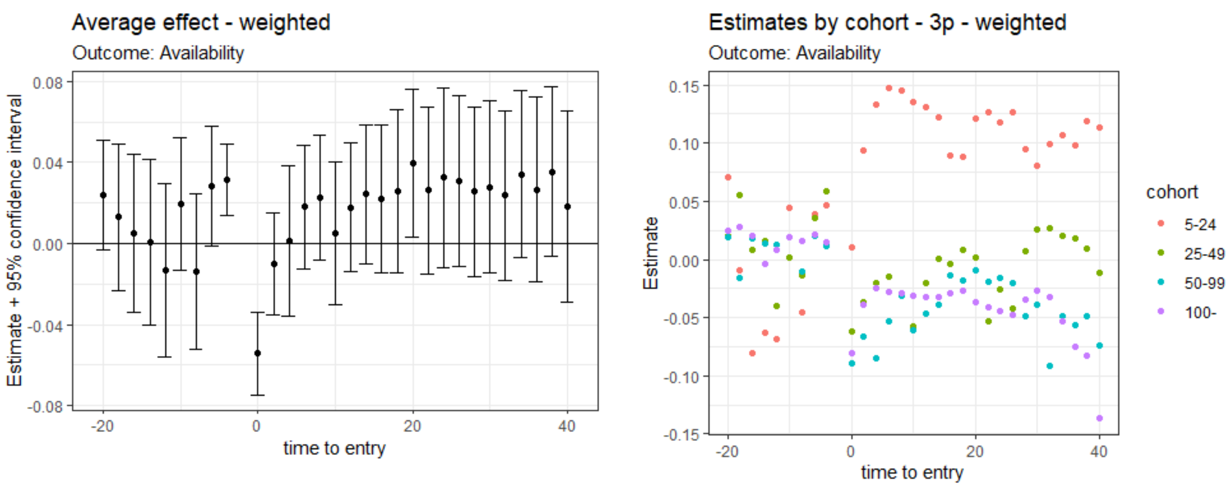
Note: Reported in the left panel are average (across product age at entry) treatment effect estimates for third-party and Amazon prices, $\hat{\tau}_{s,3P}$ and $\hat{\tau}_{s,Am}$, on the same figure. Reported in the right panel are average across-cohort "treatment effects" of Amazon entry on Amazon prices, $\hat{\tau}_{s,Am}$, by age at entry cohorts. Confidence intervals in the right panel are suppressed to foster comparability across cohorts.

Figure 9: Subcategory price effects: 3P by age cohort



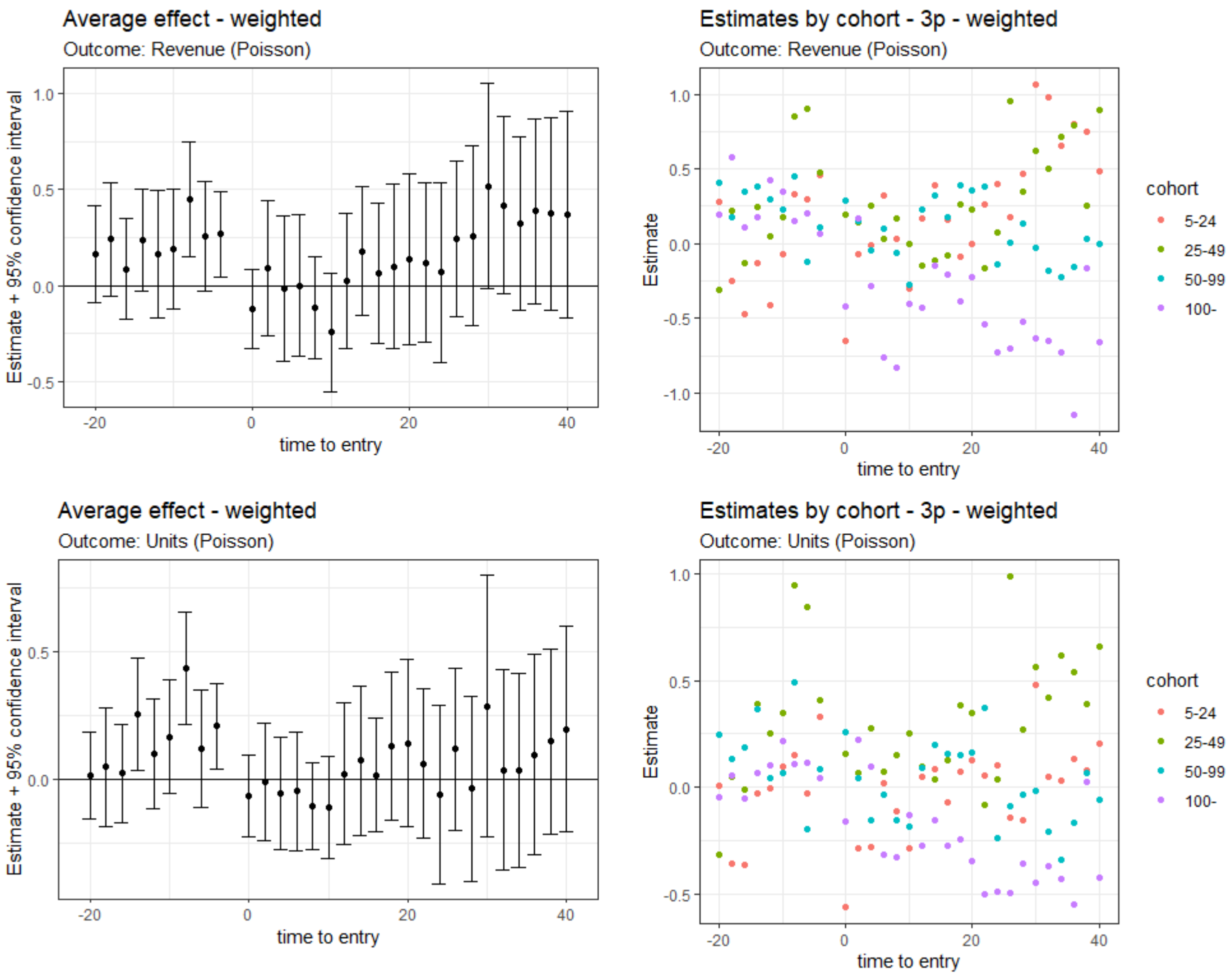
Note: Reported are the estimated common-within-age-at-entry treatment effects of Amazon entry on average third-party and Amazon prices across the 300 largest subcategories in the Home & Kitchen department. Separate effects are estimated for each subcategory for each age at entry cohort (5-24, 25-49, 50-99, and 100+ weeks); each panel reports the results for one of these four cohorts.

Figure 10: Availability effects: 3P, in aggregate and by cohort



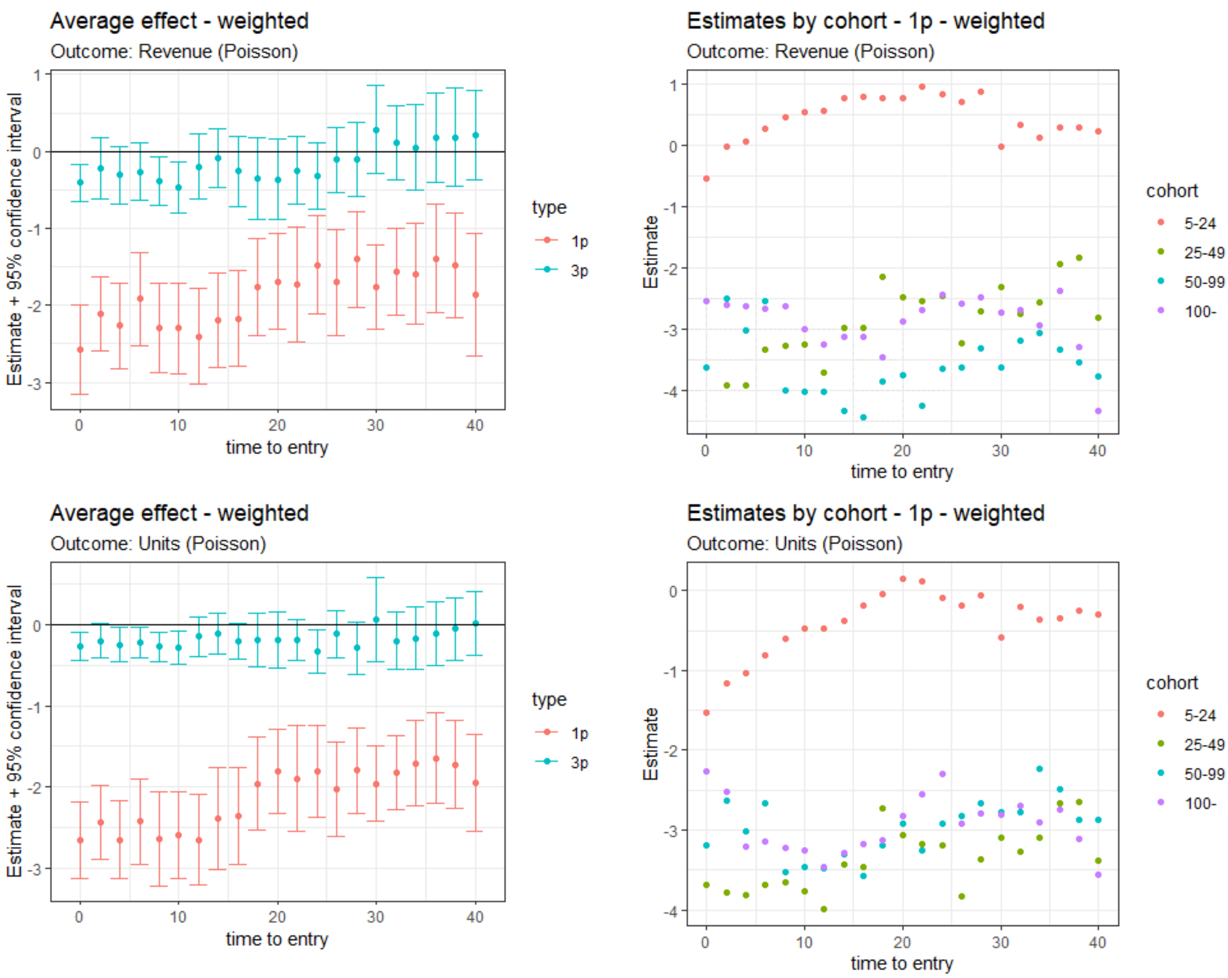
Note: Reported in the left panel are the average (across product age at entry) treatment effects of Amazon entry on average third-party normalized availability for two-week treatment windows between 20 weeks pre-Amazon entry and 40 weeks post-Amazon entry. Reported in the right panel are comparable average across-cohort treatment effects by groups of cohort weeks (with Amazon entry in 5-24, 25-49, 50-99, and 100+ weeks since a product's birth). Confidence intervals in the right panel are suppressed to foster comparability across cohorts.

Figure 11: Revenue and Quantity effects: 3P, in aggregate and by age cohort



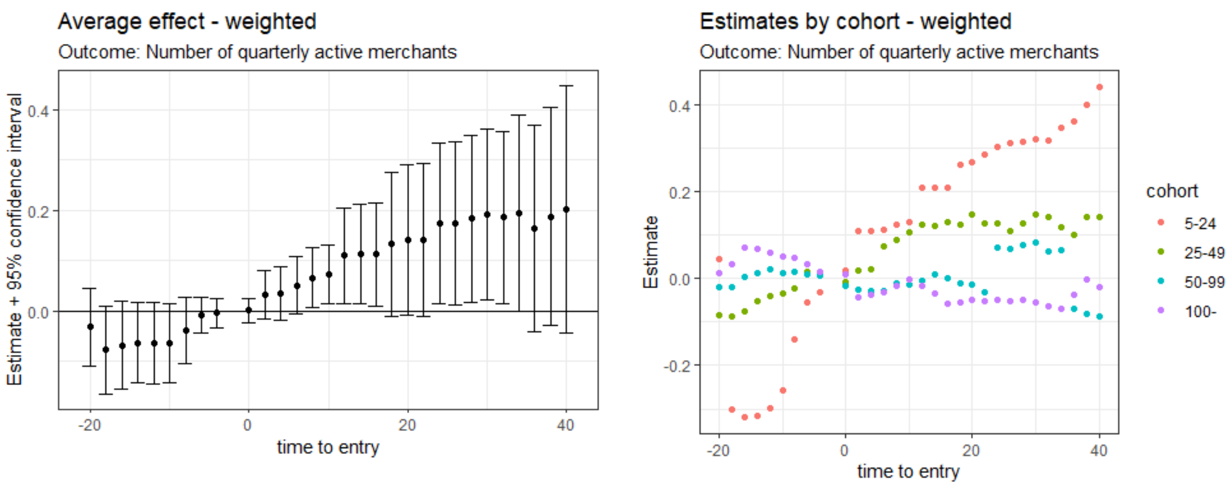
Note: Reported in the left panels are the average (across product age at entry) treatment effects of Amazon entry on average third-party normalized revenue (top panels) and quantity (bottom panels) for two-week treatment windows between 20 weeks pre-Amazon entry and 40 weeks post-Amazon entry. Reported in the right panels are comparable average across-cohort treatment effects by groups of cohort weeks (with Amazon entry in 5-24, 25-49, 50-99, and 100+ weeks since a product's birth). Confidence intervals in the right panels are suppressed to foster comparability across cohorts.

Figure 12: Revenue and Quantity effects: 3P and Amazon, and Amazon by age cohort



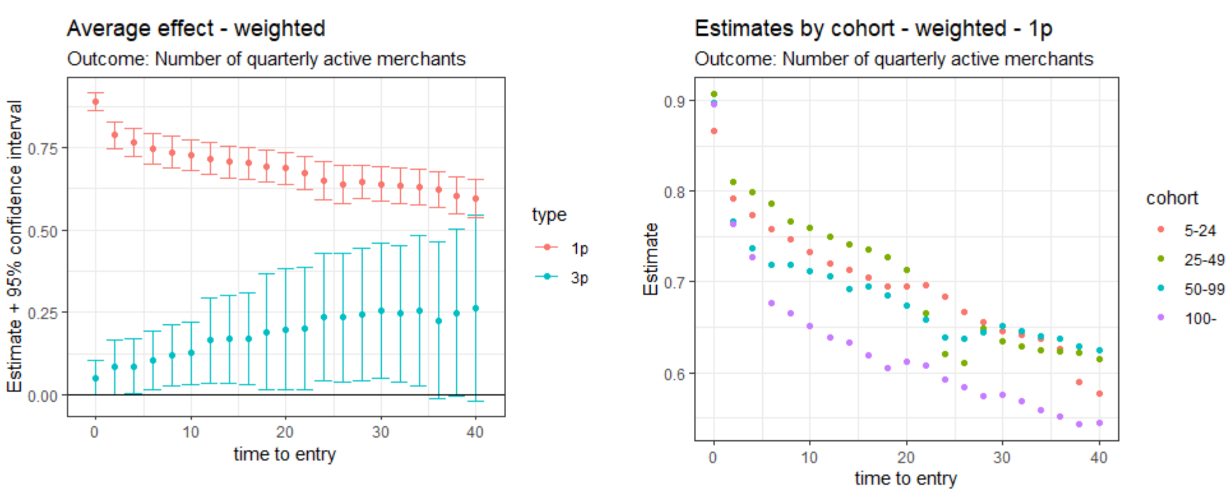
Note: Reported in the left panels are average (across product age at entry) estimated treatment effect parameters for third-party and Amazon revenue (top panels) and quantity (bottom panels). Reported in the right panels are average across-cohort "treatment effect" parameters of Amazon entry on Amazon revenue (top) and quantity (bottom) by age at entry cohorts. Table 4 imposes common effects within each age cohort and converts these estimated parameters into proportional changes. Confidence intervals in the right panels are suppressed to foster comparability across cohorts.

Figure 13: Number of Active Merchant effects: 3P in aggregate and by age cohort



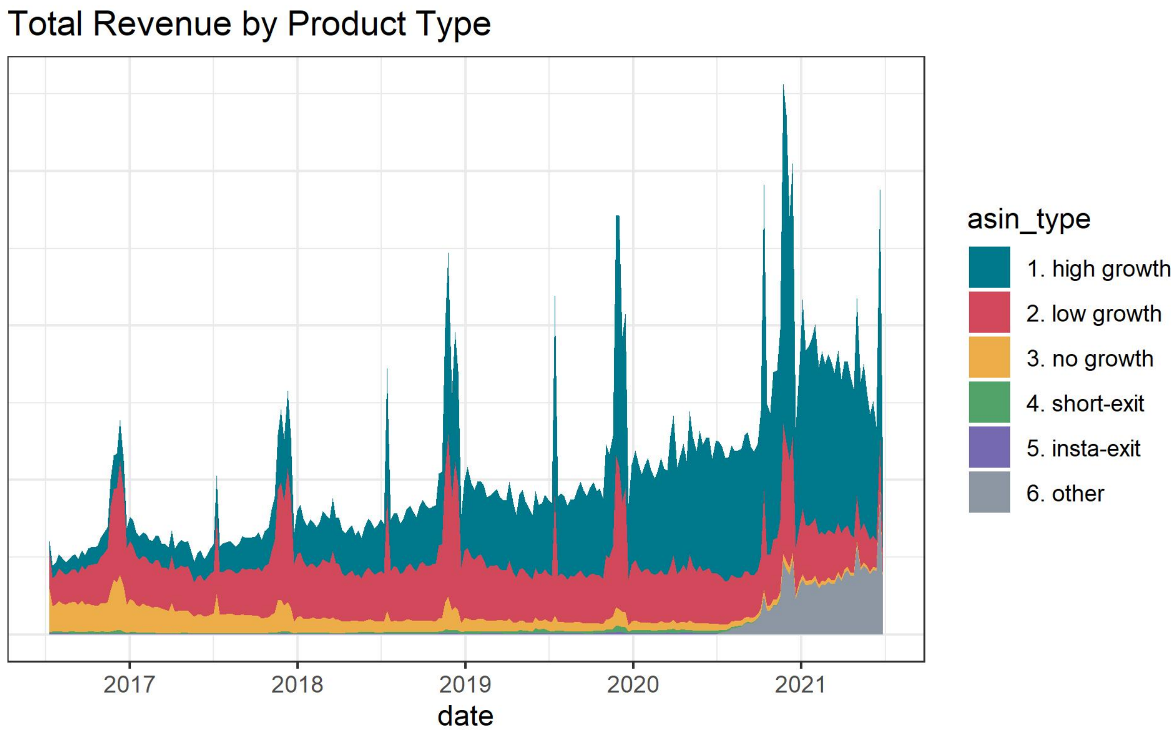
Note: Reported in the left panel are the average (across product age at entry) treatment effects of Amazon entry on the average number of quarterly-active merchants for two-week treatment windows between 20 weeks pre-Amazon entry and 40 weeks post-Amazon entry. Quarterly-active merchants are those merchants, ranked by sales, that contribute to 90% of a product's sales in that quarter. Reported in the right panel are comparable average across-cohort treatment effects by groups of cohort weeks (with Amazon entry in 5-24, 25-49, 50-99, and 100+ weeks since a product's birth). Confidence intervals in the right panels are suppressed to foster comparability across cohorts.

Figure 14: Number of Active Merchant effects: 3P and Amazon, and Amazon by age cohort



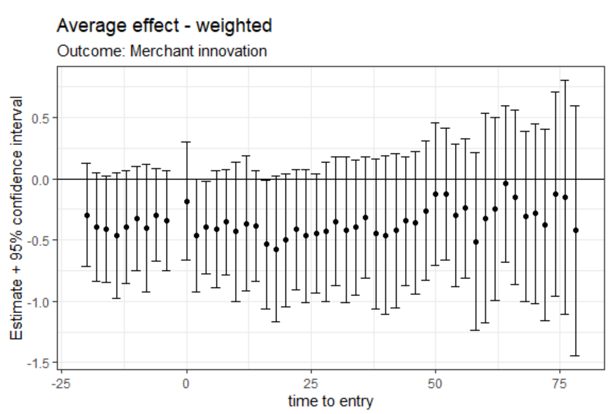
Note: Reported in the left panel are average (across product age at entry) treatment effect estimates for the average number of third-party quarterly active merchants and Amazon's continued presence offering a product. Reported in the right panel are average across-cohort "treatment effects" of Amazon entry on Amazon's continued presence offering a product by age at entry cohorts. Confidence intervals in the right panels are suppressed to foster comparability across cohorts.

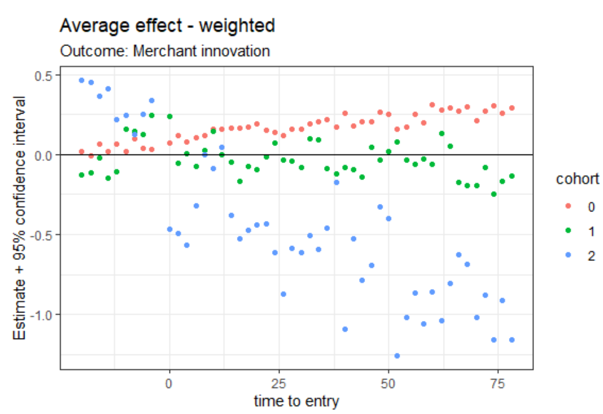
Figure 15: Product Revenue by Type, Home & Kitchen department



Note: Reported is the total revenue by product growth type in the Home & Kitchen department from July 12, 2016 to May 31, 2021. See text in the body of the paper for the definition of product growth types.

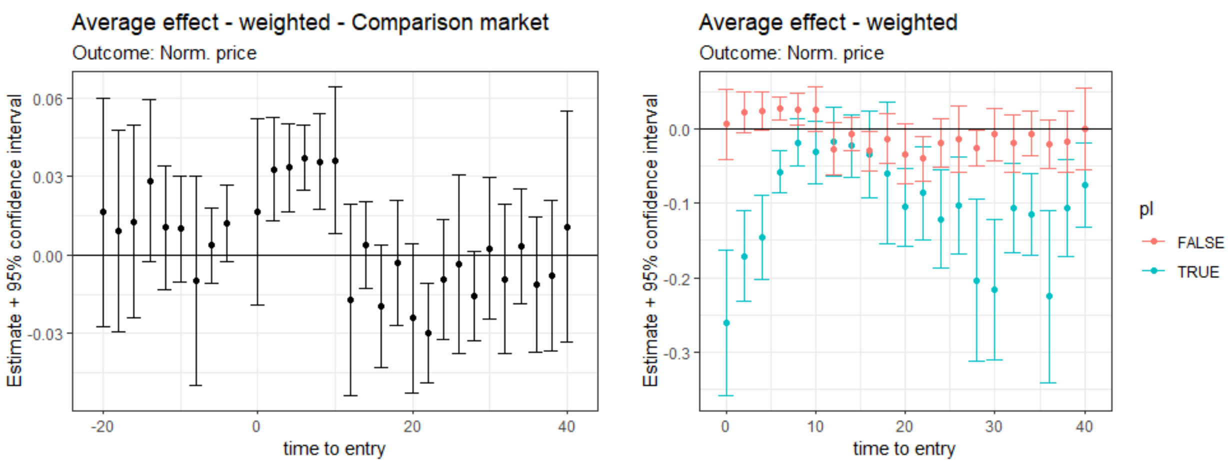
Figure 16: New product introductions effects: Fringe 3P in aggregate, and by previous high-growth product introduction cohort





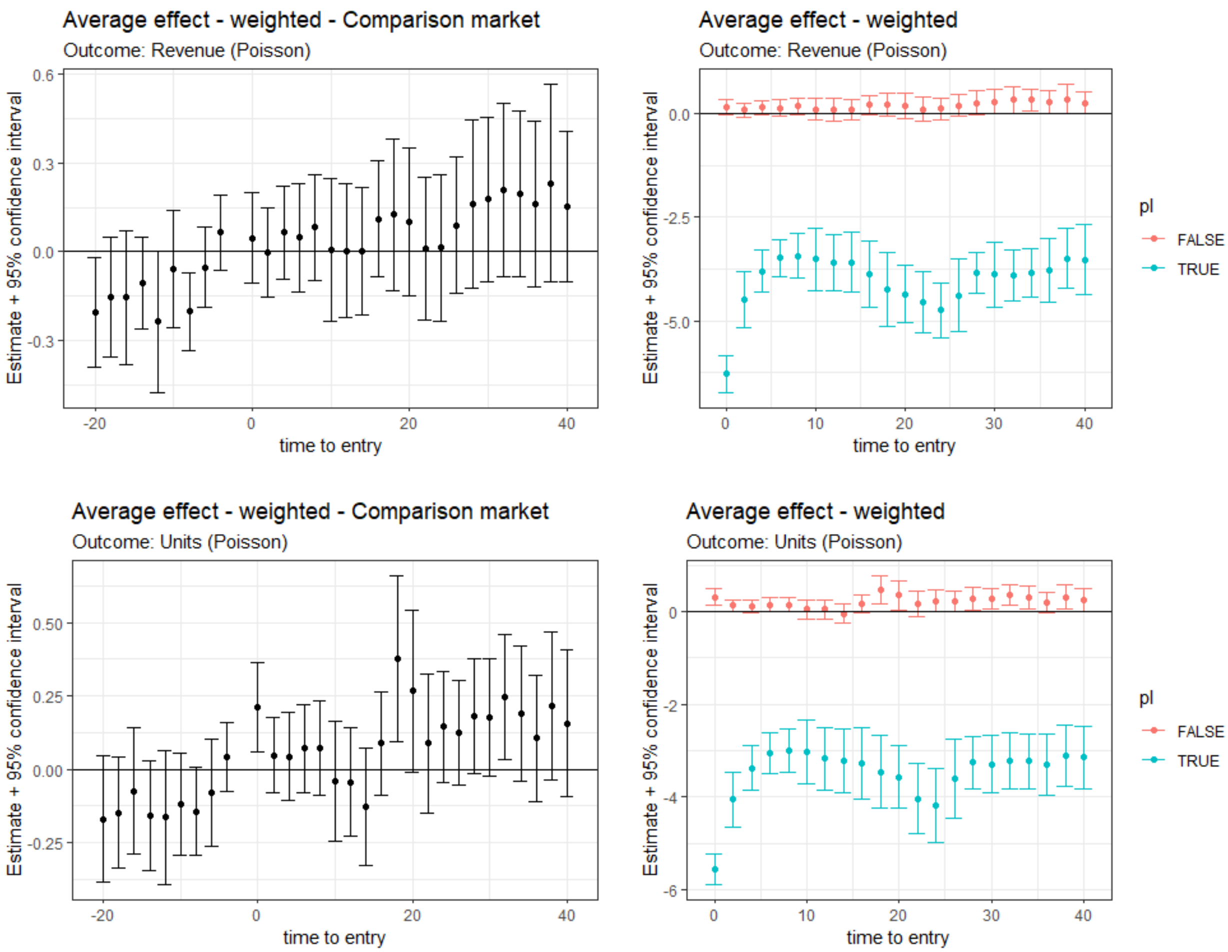
Note: Reported in the left panel are the estimated treatment effects of Amazon entry on average fringe (outside the top 100) third-party merchant new product introductions for two-week treatment windows between 20 weeks pre-Amazon entry and 80 weeks post-Amazon entry. Reported in the right panel are estimated treatment effects by previous high-growth product introduction cohorts (for merchants with 0, 1, or 2+ high-growth new products introduced previous to Amazon's entry). Confidence intervals in the right panel are suppressed to foster comparability across cohorts.

Figure 17: Private Label price effects: 3P in aggregate and relative to Amazon PL prices



Note: Reported in the left panel are the average (across product age at entry cohorts) treatment effects of Amazon Private Label entry on the average third-party normalized prices for related products for two-week treatment windows between 20 weeks pre-Amazon entry and 40 weeks post-Amazon entry. See the text for the definition of related products, the treatment group, as well as the associated control group. Reported in the right panel is the same left-panel figure as well as the average across-cohort "treatment effect" of Amazon entry on Amazon PL prices. PL = "true" corresponds average Amazon Private Label treatment effects.

Figure 18: Private Label revenue and quantity effects: 3P in aggregate, and by product age cohort



Note: Reported in the left panels are the average (across product age at entry cohorts) treatment effect parameters of Amazon Private Label entry on the total third-party revenue and quantity of related products for two-week treatment windows between 20 weeks pre-Amazon entry and 40 weeks post-Amazon entry. See the text for the definition of related products, the treatment group, as well as the associated control group. Reported in the right panels are the same left-panel figures as well as the average across-cohort "treatment effect" parameters of Amazon entry on Amazon PL revenue and quantity. PL = "true" corresponds average Amazon Private Label treatment effects. Table 10 imposes common effects within each age cohort and converts these estimated parameters into estimated proportional changes.