

The Welfare Consequences of Regulating Amazon*

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Abstract

Amazon acts as both a platform operator and seller on its platform, designing rich fee policies and offering some products direct to consumers. This flexibility may improve welfare by increasing fee discrimination and reducing double marginalization, but may decrease welfare due to incentives to foreclose rivals and raise their costs. This paper develops and estimates an equilibrium model of Amazon's retail platform to study these offsetting effects, accounting for the platform's dynamic investment incentives. The analysis yields four main results: (i) Optimal regulation is product- and platform-specific. Interventions that increase welfare in some categories, decrease welfare in others. (ii) Fee instruments are substitutes from the perspective of the platform. Interventions that ban individual instruments may be offset by the endogenous response of (existing and potentially new) instruments. (iii) Regulatory interventions have important distributional effects across platform participants. (iv) Consumers value both the Prime program and product variety. Interventions that eliminate either of the two decrease consumer as well as total welfare. By contrast, interventions that preserve Prime and product variety but increase competition – such as increasing competition in fulfillment services – may increase welfare.

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1 Introduction

Over the past 30 years, we've seen the rise of platforms as intermediaries in all kinds of transactions. A unique feature of many of these firms is that they both operate platforms and act as participants. Amazon, Wal-Mart and Target, for example, offer products directly to consumers alongside independent third-party sellers. Apple and Google create their own apps and operate App stores; and streaming companies like Spotify, Apple TV, ComCast and Netflix all sell streaming services and produce their own content.¹

This flexibility in business models can increase welfare by, for example, opening the platform to third-party sellers to increase variety (Brynjolfsson et al., 2003), or using reselling to discipline seller market power (Cabral and Xu, 2021), mitigate double marginalization (Etro, 2020), or exploit efficiency and bargaining advantages of the platform vis a vis third parties (Hagi and Wright, 2015). However, it may also decrease welfare if platforms exploit their position as operators to foreclose rivals by, for example, systematically promoting their own products or increasing commissions on third party ones to favor their own sales (Khan, 2016).

Concerns about foreclosure have increased in recent years resulting in several antitrust and regulatory investigations around the world (e.g., Committee, 2020), as well as Congressional Bills under consideration in the US that could restrict self-preferencing in hybrid platforms' (Congress, 2021a) or even ban hybrid platforms altogether (Congress, 2021b). Some countries, notably India, have already prohibited e-commerce platforms from acting as resellers.

Despite the ongoing regulatory effort, rigorous empirical analyses of the trade-offs inherent in these business models are missing from the literature. This paper aims to close this gap by providing a detailed analysis of Amazon's dual role as a seller and platform operator, and quantifying the welfare implications of proposed regulations.

I start by developing a model of a hybrid platform that plays a dual role, acting as a reseller, like Kroger, that offers products directly to consumers while also operating a marketplace, like eBay, where third-party sellers offer products to consumers in exchange for fees. Consumers choose among the products offered according to nested logit preferences over product prices, characteristics and distribution methods (i.e., Prime vs. Non-Prime delivery). Third-party sellers and wholesalers endogenously set retail and wholesale prices to maximize short-run profits. And the platform sets prices (on first-party products) and fees (on third-party products) to maximize the long-run value of the platform, which is modeled in a reduced form way by assuming that the platform's objective function combines short-run profits plus some (time-varying) weights on buyer and seller surplus.² When the weights are zero, the platform acts as a monopolist and maximizes

¹Other notable examples include (i) videogame consoles such as Nintendo Switch that sell their own games alongside third-party ones; (ii) mobile transportation companies such as Lyft that operate bike sharing and car rental programs alongside traditional taxi-like services; (iii) financial institutions that act as both market makers and participants; and (iv) credit card companies that operate payment platforms while also offering a number of ancillary services such as insurance and short term lending over the top. Related practices also appear in offline markets. For example, traditional retailers have long offered private label products and, in some cases, also operated marketplaces within their stores (e.g., BestBuy rented product booths within its stores); while regional TV networks have engaged in vertical integration as described in Crawford et al. (2018).

²These weights can be micro-founded by models of switching costs where participants regularly decide whether to stay with the platform or switch to a competitor depending on the surplus offered by the platform today. Formally, they measure the discounted marginal value of increasing buyer and seller entry by delivering higher surplus today.

short-run profits. When the weights are high, the platform sets lower prices and lower fees as a way of investing in buyer and seller acquisition. When the weights differ across participants, the platform uses the available instruments to allocate welfare across participants in a mechanism reminiscent of traditional platform theory.

The platform's business model – as encoded in vertical relationships and fee structures – determines the ability of the platform to intervene in the market. From a static perspective, the platform trades-off reselling mark-ups and marketplace fees, internalizing the cross-elasticities across products as well as the pass-through of fee changes to prices. This creates incentives to, for example, raise third-party fees to raise rivals costs or steer consumers to Amazon's own listings. From a dynamic perspective, the platform trades-off short-run profits against future gains that arise from "investing" in buyer and seller acquisition by delivering a better surplus today. This creates incentives to exploit flexibility in business models to increase or allocate welfare by, for example, using reselling to discipline seller market power or to lower prices on key products.

The main theoretical insight is that platform business models and investment incentives interact in important ways that matter for regulation. When the platform is "investing" it uses its flexibility to create and allocate surplus across participants, leaving little need for regulation. As the platform transitions to "harvesting", it begins to use its flexibility to extract surplus, making room for welfare-improving regulation.

According to the model, then, the welfare consequences of restricting hybrid platform business models are ambiguous and depend on the platform's investment incentives. As an empirical exercise, I bring the model to the data with a focus on Amazon.com.

I collect product-level data for over 100 categories from Keepa.com, and combine it with a hand-collected history of Amazon fees. I then estimate consumer demand parameters subcategory-by-subcategory in the tradition of Industrial Organization (Berry, 1994; Berry et al., 1995; Nevo, 2001). Estimation is challenging for a variety of data limitations, econometric challenges and endogeneity issues which we discuss below. In the end, I find that consumers own- and cross-price elasticities are high. Quantity-weighted average elasticities range from -4 to -8 across categories, while the within-nest correlation parameters range from 0.4-0.6 implying that consumers have strong preferences for both the platform and their nests. The resulting outside good diversion ratios — which measure the portion of consumers that leave the platform rather than switch to an inside product when prices rise — are only 30%. As a result, category-level demands are fairly inelastic ranging from -1 to -1.3.

A short-run maximizing platform facing such inelastic aggregate demands would set very high mark-ups and very high fees of approximately 40% (for the categories studied). In practice, Amazon sets much lower fees of only 22% (for the same categories). I interpret this wedge as evidence of dynamic investment incentives and use it to estimate the platform's weights on buyer and seller surplus. Specifically, I estimate supply parameters by solving the system of price and fee-setting first-order conditions to match the observed Amazon prices and fees, taking demand parameters as given. The gap between observed and short-run profit maximizing fees pins down the level of platform investment incentives, while the allocation of fees across instruments with different incidence pins down the relative weights across buyers and sellers. For the categories studied, I estimate that Amazon places 1.04 weight on consumer surplus and 0.4 weight on seller

surplus, on average.

Equipped with a fully estimated model, I explore the (medium-run) welfare consequences of several regulatory interventions.³ The first counterfactual studies the effects of imposing a "structural separation" where we split Amazon into a reseller, a logistics firm and a marketplace. Doing so eliminates foreclosure incentives but also destroys gains from coordination across the vertical chain. The hypothetical marketplace and logistics provider respond by raising fees, while the reseller lowers prices. Manufacturers benefit from the lower reseller prices, but seller, consumer and total welfare falls as a result of higher fees.

The second counterfactual considers banning reselling but expanding the Fulfillment-by-Amazon program, as was done in India. Given the estimated investment incentives, reselling is partly used to lower prices and impose pricing discipline on third-party sellers. Banning it, therefore, benefits third-party sellers at the expense of buyers and manufacturers.

The last counterfactual considers an intervention that restricts the platform from charging a mark-up on fulfillment services. This can be interpreted either as a regulation that forces Amazon to offer logistic services at cost, or as the introduction of an "as efficient" competitor that receives the Prime checkmark⁴ and competes the mark-up away. This preserves the gains from Prime but enables competition in fulfillment services. The policy increases welfare, but only slightly as other fees endogenously respond to offset the regulation.

The analysis offers four generalizable lessons: first, hybrid platform business models are not *a priori* harmful. When competition is robust and the platform exhibits high investment incentives, flexibility in business models may increase welfare. As a result, optimal regulation is product- and platform-specific and depends on the extent of competition. Second, all participants, including the platform, respond endogenously to interventions. When platforms have multiple fee instruments (as in the case of Amazon), interventions may be partially or fully offset by the endogenous response of the platform. Third, interventions have important distributional consequences across platform participants. Last, consumers value both the Prime program and product variety. Interventions that eliminate either of the two decrease consumer as well as total welfare. By contrast, interventions that preserve Prime and product variety but increase competition – such as increasing competition in fulfillment services – may increase welfare.

Related Literature. This paper contributes to a long literature on platform theory (Rohlfis, 1974; Katz and Shapiro, 1985, 1994; Farrell and Katz, 2003; Rochet and Tirole, 2003; Armstrong, 2006). In fact, our marketplace model can be viewed as a special case of the canonical framework of Rochet and Tirole (2006), where we explicitly model the trade of goods under symmetrically differentiated competition; and we allow the platform to set a general set of fees. Explicitly modeling the trade of goods helps us clarify how platform incentives relate to supply and demand primitives; and allows us to discipline the model using traditional tools from empirical Industrial Organization.

Within the platform literature, this paper is closest to a growing literature focused on the business mod-

³I focus on the main counterfactuals here, but provide additional ones in Section 6.

⁴This could be achieved through the (forced) introduction of a Seller Fulfilled Prime program, which requires Amazon to give the Prime checkmark to any seller who consistently meets pre-defined performance metrics. Amazon nominally operates such a program, but it has been progressively restricted over the last few years.

els, behavior and regulation of trade platforms. [Hagiu \(2009\)](#) and [Anderson and Bedre-Defolie \(2017\)](#) study optimal pricing and variety provisioning by marketplace platforms. [Hagiu and Wright \(2015\)](#); [Hagiu et al. \(2020\)](#); [Etro \(2020\)](#) study the trade-offs and determinants of marketplace vis a vis reseller intermediation, with a focus on platform cost and selling advantages. [Zhu and Liu \(2018\)](#) investigate this question empirically, showing that transition into Prime decreases sales ranks. [Jiang et al. \(2011\)](#), [Etro \(2020\)](#) and [Anderson and Bedre-Defolie \(2020\)](#) analyze platforms that face a trade-off between extracting rents and motivating innovation by third-party complementors. Last, a few papers study intermediary steering incentives ([Cornière and Taylor, 2019](#); [Chen and Tsai, 2021](#); [Cure et al., 2021](#); [Johnson et al., 2020](#)), sometimes in the context of data sharing ([Kirpalani and Philippon, 2021](#)); as well as the profit and welfare implications of platform price-parity agreements ([Gomes and Mantovani, 2020](#); [Liu et al., 2021](#)).

Different features of the platform relate to four other literatures. (a) The marketplace model is based on insights from the incidence and optimal taxation literatures (see, for example, [Marshall, 1890](#); [Anderson et al., 2001](#); [Hamilton, 2009](#); [Weyl and Fabinger, 2013](#); [Peitz and Reisinger, 2014](#); [Adachi and Fabinger, 2020](#)), though we focus on a profit-maximizing platform as opposed to a welfare-maximizing government. (b) The reseller model thinks of Amazon as a multi-product intermediary, as in [Forbes \(1988\)](#); [Mulhern and Leone \(1991\)](#); [Rhodes \(2014\)](#); [Rhodes et al. \(2021\)](#). Like [Rhodes et al. \(2021\)](#), it features incentives for the platform to lower prices on products with higher pass-through and raise prices on products with lower pass-through. (c) The paper can also be interpreted as contrasting the welfare consequences of wholesaler vs. marketplace relationships in the tradition of [Villas-Boas \(2007\)](#). (d) Last, since the platform uses alternate fee structures and distribution methods to optimally price discriminate, the paper relates to a long literature on price discrimination (see, for example, [Varian, 1985](#); [Aguirre et al., 2010](#)).

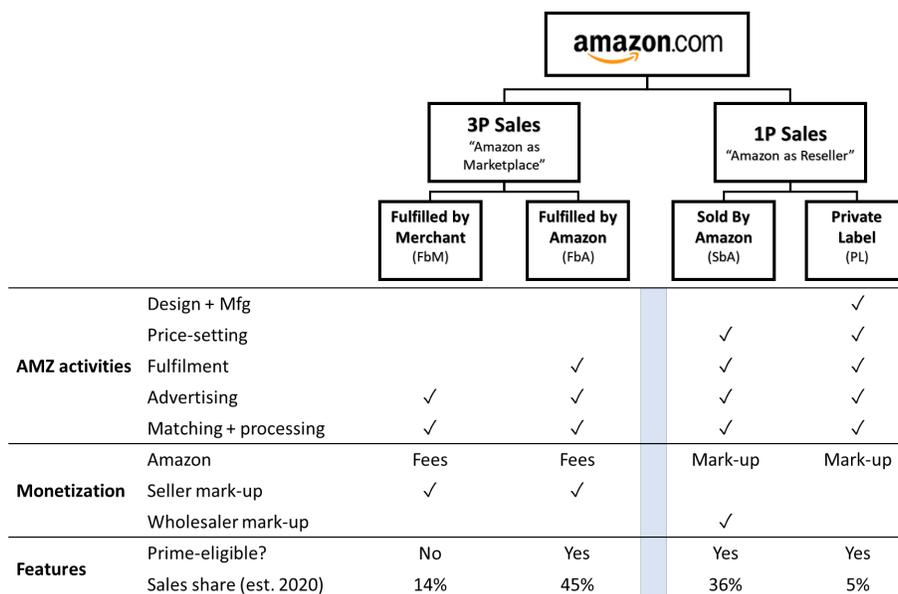
From a methodological perspective, this paper contributes to literatures on supply and demand estimation. Following the seminal work of [Berry \(1994\)](#), the demand estimation literature has mostly focused on random coefficients models estimated as in [Berry et al. \(1995\)](#); [Nevo \(2001\)](#). We take a different approach due to data limitations, and instead estimate a nested logit model. Rather than making arbitrary assumptions for nests, however, we exploit the Grouped Fixed Effects estimator of [Bonhomme et al. \(2019\)](#) and [Almagro and Manresa \(2021\)](#) to recover the nest structure from the data. In addition, we deal with the zeroes of demand problem by following [Gandhi et al. \(2020\)](#). [Dubé et al. \(2020\)](#) and [Li \(2019\)](#) present alternate approaches for dealing with this problem.⁵

On the supply side, our paper relates to a long literature that empirically analyzes the price and welfare implications of vertical relationships ([Villas-Boas, 2007](#); [Bonnet and Dubois, 2010](#); [Crawford et al., 2018](#); [Conlon and Mortimer, 2021](#)), often in the context of private label products (e.g., [Chintagunta et al. \(2002\)](#); [Ellickson et al. \(2018\)](#)). The closest paper is perhaps [Crawford et al. \(2018\)](#) which emphasizes the trade-off between potential efficiency gains from vertical integration against potential welfare losses from foreclosure incentives.

At a high level, this paper also speaks to the rise and welfare consequences of e-commerce. The initial literature focused on contrasting online and offline commerce and quantifying the gains from e-commerce.

⁵[Dubé et al. \(2020\)](#) introduce a pairwise-difference approach that constructs moment conditions based on differences in demand between pairs of products. [Li \(2019\)](#) uses a parametric empirical Bayes estimator, which uses information in other markets to generate strictly positive posterior estimates of the purchase probabilities.

Figure 1: Overview of Amazon’s Retail Platform



Hortacsu and Syverson (2015) provide a good introduction to aggregate trends. Brynjolfsson and Smith (2000) and Cavallo (2017) compare online and offline prices. Brynjolfsson and Smith (2001) study the importance of online retailer brands in the presence of price comparison sites. Brynjolfsson et al. (2011) discuss how the aggregation of consumers into a single national platform, combined with powerful search tools and recommendation systems gave rise to the “long tail” – the impressive variety of online offerings. Brynjolfsson et al. (2003) estimate gains from product variety in the books category. Quan and Williams (2018) emphasize the importance of across-market demand heterogeneity and the “zeroes of demand” problem for estimates of gains from variety. Accounting for these factors reduces gains from variety in the shoes category by 45%. Dolfen et al. (2019) revisit these estimates using credit card data, while also emphasizing gains from convenience. Cabral and Xu (2021) study price-gouging incentives. More recent papers emphasize the welfare costs of winner-take-all dynamics (Khan, 2016, 2018, 2019).

2 Setting

The empirical analysis focuses on Amazon.com, the world’s largest retail e-commerce platform with total US sales reaching nearly \$300 billion in 2019 or 7.7% of total retail sales. I begin by providing an overview of the platform before developing a model that incorporates the salient features.

Distribution channels. Figure 1 provides an overview of Amazon’s distribution channels, including the activities undertaken by the platform vis a vis sellers along with the platform’s monetization strategies.⁶ I divide the platform into a marketplace where Amazon offers services to sellers in exchange for fees; and a

⁶We exclude other businesses such as Whole Foods, Prime Video and Amazon Web Services, since they are outside the scope of this paper.

reseller which offers products directly to consumers.

Within the marketplace, sales may be fulfilled by the merchant (FbM) or fulfillment by Amazon (FbA). Under FbM, Amazon functions as a pure marketplace, like Ebay under fixed price offerings. In exchange for matching buyers and sellers and processing the transaction, Amazon charges an ad-valorem “referral fee” ranging from 6% to 45% of the selling price (including shipping), depending on the product category. The seller sets prices and controls the inventory and fulfillment processes – meaning they stock products on their own warehouses and ship them directly to the buyer upon sale.⁷ Since sellers ship the items, FbM products are *not* eligible for 2-day Prime or Free Super Saver shipping (for non-prime customers). Instead, sellers may choose to charge a shipping fee or provide free shipping. They also provide the customer service and set their own refund and return policy.⁸ Seller behavior is governed by the Amazon Seller Agreement, which sets limits on pricing, and outlines minimum levels of customer service and return policies. The Seller Agreement also prohibits the sale of counterfeits and requires sellers to abide by Minimum Advertised Prices (MAP) set by manufactures, though complaints of violations abound (e.g., [Stone \(2013\)](#)).

Under FbA, sellers contract Amazon for fulfillment. They send their inventory in bulk to Amazon fulfillment centers, where they are stored until sale. Upon sale, Amazon handles the shipping, customer service, refunds, and returns for the products – following Amazon’s own processes and policies. FbA, therefore, is essentially equivalent to SbA from the *buyers* perspective: FbA products are eligible for 2-day Prime shipping as well as Free Super Saver Shipping and, since Amazon handles the returns, returns are as easy as for SbA products. Amazon even informs sellers that “to ensure a great customer experience, we may accept returns beyond the time-frame stated in these policies” ([link](#), accessed on June 4, 2020).

Within the reseller, I separate externally branded products sold-by-Amazon (SbA) and private label products (PL). Under SbA, Amazon functions as an online retailer: it purchases products at wholesale prices from producers and sells them directly to consumers. Amazon takes charge of the pricing, shipping, customer service, refunds, and returns for those products – following its own policies. SbA products are eligible for 2-day Prime and Free Super Saver Shipping.

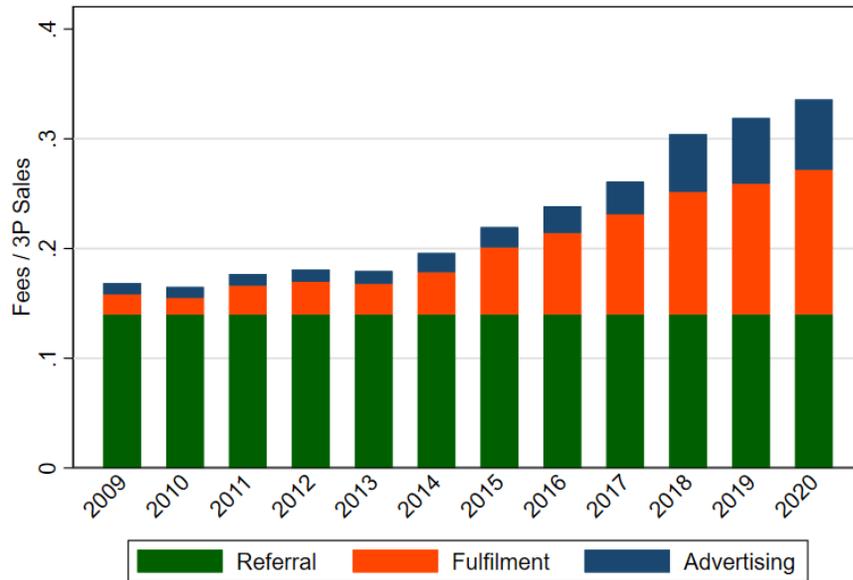
Last, under PL, Amazon not only sells the products but it also designs and markets them under private label or exclusive brands. Most PL sales are in consumer electronics – such as the Kindle, the Fire TV and Alexa-enabled speakers – but Amazon also offers thousands of products under hundreds of brands such as AmazonBasics, AmazonCollection, Pinzon and Mama Bear.

Monetization. Amazon monetizes 1P sales based on a mark-up over wholesale costs. Amazon monetizes 3P transactions by charging three types of fees: referral fees for matching and processing, fulfillment fees for FbA and advertising fees. Matching and processing fees apply to all 3P transactions and are set at ~15% of the selling price (including shipping), on average. Fulfillment fees apply only to FbA products. They include a monthly inventory storage fee (which varies throughout the year) plus a per-unit fulfillment fee based on the dimensions and weight of the item. The pseudo-fixed cost implies that only items with relatively high sales will be attractive under FbA. Last, advertising fees apply on a product-by-product basis

⁷Sellers may enlist a third-party to fulfill orders on their behalf, though Amazon has very specific policies around this practice.

⁸According to Amazon, most sellers on the platform offer a returns policy equivalent to Amazon’s, which offers free returns for items within 30 days of receipt of shipment ([link](#), accessed on June 4, 2020).

Figure 2: 3P Fees as a % of 3P Sales, overall and by distribution channel



Source: Analyses from Amazon disclosures

Source: compiled by the author from Amazon disclosures.

depending on seller decisions.

Figure 2 shows the evolution of 3P fees over time, by type of fee. 3P fees as a share of revenues nearly doubled since 2009, from 17% to 32%. Referral fees remained largely stable, so that the increase is almost entirely explained by a rise in Fulfillment and Advertising fees. Total fulfillment fees increased from less than 1% in 2009 to nearly 12% in 2020. Most of the increase is driven by a composition effect that accounts for the growth of the FbA program while holding FbA fees fixed at their initial level. However, a significant portion of the increase is due to a near doubling of FbA fees since 2009. Last, advertising fees increased from less than 1% of 3P sales in 2009 to nearly 5% in 2020.

3 Model

Let us now develop a model of Amazon that incorporates the salient features described above. Figure 3 provides an overview of the model, which should be interpreted as applying at the level of a narrow product subcategory k . I take product subcategories from the Amazon product tree, which contains more than 44,000 subcategories. Sample subcategories include ‘irons’ and ‘baby wipes and refills’.

Consumers visit the website to choose among the offered products j according to nested logit preferences over product prices, characteristics and distribution methods (i.e., Prime vs. Non-Prime delivery). The key parameters governing consumer demand are the disutility of price α , a preference for Prime fulfillment ζ and within-nest correlations σ . All of these parameters are estimated from the data, separately for each product subcategory. When consumers purchase a good, they pay a price p_j which gets distributed between the platform and participants depending on the nature of vertical relationships. When products are sold by

α^k measures the consumer price sensitivity in subcategory k . ζ^k measures consumer preferences for Prime fulfillment – interpreted as a bundle of services including 2-day shipping and Amazon’s return policy, for example. Since several regulatory interventions involve banning Prime, this parameter will feature prominently in counter-factuals.¹⁰ x_{jt} is a $1 \times K$ vector of additional product and seller characteristics for product j in week t including, for example, product ratings and reviews. Last, $\varepsilon_{ijt} = \eta_{g(j)t}^k + \tilde{\varepsilon}_{ijt}$ is an idiosyncratic taste shock assumed to vary unobservably over individuals i . $g(j)$ denotes the nest to which product j belongs so that the idiosyncratic taste shock is correlated among products in the same nest. This induces a correlation structure in the covariance matrix across products so that products in the same nest exhibit higher cross-elasticities than products across nests. To simplify notation, I omit subscripts t, k in the rest of this section.

Assuming that ε_{ijt} has the appropriate distribution so that the resulting model is the nested logit, we obtain closed-form solution probabilities:

$$\begin{aligned}
 P_j &= \frac{e^{V_j/\lambda_g} \left(\sum_{l \in J_g} e^{V_l/\lambda_g} \right)^{\lambda_g - 1}}{1 + \sum_{h=1}^G \left(\sum_{l \in J_h} e^{V_l/\lambda_h} \right)^{\lambda_h}}, \\
 &= \underbrace{\frac{e^{V_j/\lambda_g}}{\left(\sum_{l \in J_g} e^{V_l/\lambda_g} \right)}}_{P_{j|g}} \cdot \underbrace{\frac{\left(\sum_{l \in J_g} e^{V_l/\lambda_g} \right)^{\lambda_g}}{1 + \sum_{h=1}^G \left(\sum_{l \in J_h} e^{V_l/\lambda_h} \right)^{\lambda_h}}}_{P_g},
 \end{aligned} \tag{1}$$

where we assume the outside good belongs to its own nest and has utility of 0. This shows that the Nested Logit model can be thought of as a sequential choice: consumers first choose a nest with probability, P_g , and then a product within the nest with probability, $P_{j|g}$. The key parameter (roughly) governing within group correlation is λ_g . When $\lambda_g = 1$, the model simplifies to the multinomial logit and cross-elasticities across all products exhibit Independence of Irrelevant Alternatives. As $\lambda \rightarrow 0$, consumers always stay within their nest.

The expected surplus from choosing nest g is given by the logit inclusive value of the nest, adjusted for λ_g :

$$A_g = \lambda_g \log \sum_{j \in J_g} e^{V_j/\lambda_g}.$$

The aggregate consumer surplus, CS , is then obtained by choosing across nests:

$$CS = \log \sum_g e^{A_g}$$

¹⁰This parameter is reminiscent of the dominant firm advantages parameter in [Cabral \(2018\)](#). We assume that the estimated preferences for Prime fully translate into utility gains. This may be an over-estimation if Amazon’s algorithms steer consumers towards Prime-eligible products (e.g., through the BuyBox). We hope to explore this in future versions.

3.2 Platform

Let us now describe the problem of the platform. I start with a general model of platform interventions before specifying the structure for the case of Amazon.

3.2.1 General Model

Consider a general hybrid platform that faces a dynamic optimization problem given by

$$\max_{\mathbf{f}} V(\Theta, \mathbf{f}) = \Pi(\Theta, \mathbf{f}) + \delta \tilde{V}(\Theta, \mathbf{f}).$$

where the firm's value function V , short-run profits Π and continuation value \tilde{V} depend on state variables Θ and the choice of policy instruments \mathbf{f} . For now, \mathbf{f} can be general and include prices on first-party products, fees on third-party products or richer interventions such as the introduction of private label products or the use of algorithms that steer buyers across products.

Maximization with respect to a given policy instrument f_m implies:

$$\frac{\partial \Pi(\Theta, \mathbf{f})}{\partial f_m} + \delta \frac{\partial V(\tilde{\Theta}, \mathbf{f})}{\partial f_m} = 0,$$

which shows that the platform trades-off short-run profits against long-run gains.

Suppose now that the firm's continuation value depends on current choices only through the surplus delivered to each side of the platform. This is true, for example, in models of switching costs where the state variable is the number (or share) of buyers and sellers and participants make entry decisions depending on the surplus delivered today $N_{t+1}^b = f(CS_t, \Theta_t)$ and $N_{t+1}^s = f(SS_t, \Theta_t)$.¹¹ In that case, the first-order-condition can be written as:

$$\frac{\partial \Pi(\Theta, \mathbf{f})}{\partial f_m} + \underbrace{\delta \frac{\partial V(\Theta, \mathbf{f})}{\partial N^b} \frac{\partial N^b}{\partial CS}}_{\gamma^c} \frac{\partial CS(\Theta, \mathbf{f})}{\partial f_m} + \underbrace{\delta \frac{\partial V(\Theta, \mathbf{f})}{\partial N^s} \frac{\partial N^s}{\partial SS}}_{\gamma^s} \frac{\partial SS(\Theta, \mathbf{f})}{\partial f_m} = 0,$$

where I define $\gamma^c = \delta \frac{\partial V}{\partial N^b} \frac{\partial N^b}{\partial CS}$ and $\gamma^s = \delta \frac{\partial V}{\partial N^s} \frac{\partial N^s}{\partial SS}$ as reduced form parameters that measure two-sided dynamic investment incentives. These parameters have an intuitive interpretation: they measure of the discounted marginal gains in future value that arise from delivering higher surplus today. They depend on the firm's discount rate, the marginal elasticity of long-run value to buyer/seller entry and, crucially, the buyer and seller entry (semi-)elasticities. Nascent firms or firms that face higher entry elasticities, then, can be expected to have higher investment incentives.

Since both value functions and entry elasticities are state dependent, the platform's dynamic incentives γ^j are state dependent. One option to proceed would be to fully specify a value function and entry process and analyze how these evolve over time. However, this is a challenging task that deviates from my focus on

¹¹ Similar features also appear in models of search and models of asymmetric information where sellers make entry decision without knowledge of the quality of their product. All of these features seem to closely relate to the case of Amazon.

understanding the welfare trade-offs inherent in hybrid platform business model.

To simplify the analysis, I treat γ^j as reduced form parameters and estimate them from the data. Formally, I assume that the platform's objective function maximizes a weighted of sum of short-run profits and (state-dependent) weights on buyer and seller surplus:

$$\max_{\mathbf{f}_t} V(N^b, N^s) = \Pi(\mathbf{f}; \Theta) + \gamma^c CS + \gamma^s SS.$$

The first order condition can be written as:

$$\frac{\partial \Pi(\Theta, f)}{\partial f_m} = -\gamma^c \frac{\partial CS(\Theta, f)}{\partial f_m} - \gamma^s \frac{\partial SS(\Theta, f)}{\partial f_m},$$

which shows that the platform trades-off short-run profits against long-run investments. When $\gamma^c = \gamma^s = 0$, the platform maximizes short-run profits. When γ^c, γ^s are high, the platform sets lower prices and lower fees as a way of investing in future value. Last, when $\gamma^c > \gamma^s$, the platform uses the available instruments to allocate surplus towards consumers, in a mechanism reminiscent of traditional platform theory (Rochet and Tirole, 2003).

The welfare consequences of adjusting business models by introducing new instruments or restricting existing ones are, therefore, ambiguous. They depend on the initial platform business model (i.e., the set of available policy variables) as well as the platform's investment incentives.

3.2.2 Amazon Problem

To bring the model to the data, then, I must specify a set of instruments \mathbf{f} . I focus on trade-offs inherent in different forms of vertical relationships given the importance of rising fees for Amazon's profitability, but similar analyses could be performed to study algorithmic choices, for example. I assume that Amazon maximizes

$$\max_{p_j \in 1P, \tau^u, \tau^v} \Pi^A = \sum_{j \in 1P} \underbrace{(p_j - \hat{w}_j) s_j(\mathbf{p})}_{1P \text{ profits}} + \sum_{l \in 3P} \left(\underbrace{u_l s_l(\mathbf{p})}_{\text{Unit fees}} + \underbrace{v_l p_l s_l(\mathbf{p})}_{\text{Ad-valorem fees}} \right) + \underbrace{\gamma^b CS(\mathbf{p})}_{\text{Consumer surplus}} + \underbrace{\gamma^s SS(\mathbf{p})}_{\text{Seller surplus}}, \quad (2)$$

where \hat{w}_j denotes the effective marginal cost of the platform accounting for fulfilment. For SbA products, $\hat{w} = w + f^A$, which depends on an endogenous wholesale price w set by wholesalers. For PL products, $\hat{w} = c + f^A$. $s_j(\mathbf{p})$ denotes the share (in quantities) of product j given a vector of prices \mathbf{p} , which depends on the distribution method of product j according to consumer preferences for Prime, ζ . The first term captures profits from 1P products, which depend on a mark-up over effective marginal cost. The next two terms capture revenues from unit and ad-valorem fees, u_j and v_j , which are further specified below. The last two terms put weight $\gamma^j \in (0, \infty)$ on buyer and seller surplus, to account for dynamic investment incentives of the platform.

This specification incorporates four key trade-offs inherent in Amazon's business model.

First, within the marketplace, flexibility in fee structures governs the platform’s ability to price discriminate on third-party products and to endogenously respond to regulatory interventions. A fully heterogeneous set of fees would allow the platform to optimally allocate surplus, but it may be difficult to implement in practice due to operational (e.g., it may be hard to set or enforce negative and/or highly heterogeneous fees) or strategic concerns (e.g., fees may have anchored seller and regulatory expectations, so that changing them may be too costly). In fact, many of the largest platforms still use a single ad-valorem fee for all products and categories (e.g., Etsy). To closely mirror the platform – in both estimation and counter-factuals – I take the set of fee instruments from the data and only allow the platform to adjust the level of those instruments in response to regulation. Specifically, I assume that unit and ad-valorem fees are given by

$$v = \tau^r V \quad \text{and} \quad u = \tau^u U$$

where $V = [v_1, \dots, v_{N^v}]$ and $U = [u_1, \dots, u_{N^u}]$ are $J \times N^v$ and $J \times N^u$ matrices of ad-valorem and unit fee instruments, respectively; and τ^r, τ^u are $1 \times N^v$ and $1 \times N^u$ vectors of loadings on the corresponding instruments. I then define V and U to mirror the fee structures used by Amazon. For example, in the categories that we explore, Amazon charges a 15% ad-valorem referral fee for products with a price above \$10 and an 8% fee for products below \$10. I set V to include a vector equal to 0 for first-party products, 0.15 for third-party products with a price above \$10, and 0.08 for third-party products with a price of 0.08. In the baseline, $\tau^v = 1$ and we recover the right fees. In counter-factuals, I allow the platform to adjust only τ^v .¹²

Second, the availability of reselling intermediation can alter the allocation of surplus in four ways: (a) reselling transfers responsibility of the selling and fulfillment process to Amazon. If Amazon has selling, bargaining or cost advantages vis a vis third parties, this increases welfare (and vice versa). (b) Reselling (may) mitigate double marginalization by supporting richer bargaining arrangements such as two-parts tariffs, or by allowing Amazon to replace an independent third-party seller by purchasing directly from the manufacturer. The latter turns a triple-marginalization problem (Amazon, seller, producer) into a double-marginalization problem (Amazon, producer), which improves consumer, producer and platform welfare at the expense of seller welfare. (c) Reselling transfers pricing power to the platform, which allows it to optimally price discriminate instead of relying on shared fee-policies. Depending on the product and the platform’s investment incentives, this can lead to lower or higher prices. (d) Reselling changes the order of marginalization. Under marketplace intermediation, the platform sets fees first, depending on *seller* pass-through. Under reselling, the wholesaler sets mark-ups first, depending on *platform* pass-through. To the extent that platform and seller pass-through differ from one and from each other, transitions to and from reselling re-allocate welfare across participants.

Third, reselling mark-ups and marketplace fees are substitutes from the perspective of the platform so the platform will internalize cross-elasticities when setting prices and fees. This creates incentives to foreclose rivals by, for example, raising third-party fees to raise rivals cost; but it also allows the platform to use

¹²I focus on explicit unit and ad valorem fees in this paper. However, as described by [Weyl and Fabinger \(2013\)](#) and [Adachi and Fabinger \(2020\)](#), many interventions ranging from exogenous competition to selling advantages enter third-party seller’s problem as a mixture of unit and ad-valorem taxation. They could, therefore, be easily incorporated into our framework.

reselling to discipline seller market power by setting lower prices on key products.

Last, and perhaps most importantly, all of these trade-offs interact with (and are in fact disciplined by) the platform's dynamic investment incentives. When γ^c and γ^s are high, the platform will use flexibility in fee structures, vertical relationships and internalization to improve the quality of the platform. As γ^c and γ^s fall, however, the platform begins to exploit its flexibility to extract surplus.

3.2.3 First-Party Price-setting

Let us now derive the platform's first-order-conditions, starting with 1P price-setting. The first order condition of equation (2) with respect to $p_j : j \in SBA$ is given by:

$$s_j(\mathbf{p}) + \sum_{k \in SBA} (p_k - \hat{w}_k) \frac{\partial s_k}{\partial p_j} + \sum_{l \in 3P} \left(u_l \frac{\partial s_l}{\partial p_j} + v_l p_l \frac{\partial s_l}{\partial p_j} \right) + \gamma^c \frac{\partial CS(\mathbf{p})}{\partial p_j} + \gamma^s \frac{\partial SS(\mathbf{p})}{\partial p_j} = 0,$$

where \hat{w}_j denotes the effective marginal cost described above. The first two terms are standard for a multi-product retailer. They show that the platform trades-off increased revenues from higher prices (first term) against decreased revenues from lower quantities, accounting for cross-elasticities across 1P products (second term). The next two terms are new, however. The first one accounts for unit and ad-valorem fees collected on 3P products, to the extent that consumers switch to purchase them. This leads to higher mark-ups vis a vis a pure reseller. The last two terms measure the buyer and seller welfare loss from raising prices, and are weighted by the platform's investment incentive parameters, γ^c and γ^s . They imply that the platform will optimally set lower prices when γ^b is high or products contribute more to consumer surplus; and lower prices when γ^s is high or decreasing prices leads to a larger decline in seller surplus.

Stacking these conditions into a matrix, we obtain the optimal pricing policy

$$\mathbf{p} - \hat{\mathbf{w}} = (\mathbf{A} \odot \mathbf{\Omega})^{-1} \left(\mathbf{s}(\mathbf{p}) - (\mathbf{B} \odot \mathbf{\Omega}) (\mathbf{u} + \mathbf{v} \odot \mathbf{p}) + \gamma^c \frac{\partial CS(\mathbf{p})}{\partial \mathbf{p}} + \gamma^s \frac{\partial SS(\mathbf{p})}{\partial \mathbf{p}} \right), \quad (3)$$

where \mathbf{A} accounts for cross-ownership of multi-product sellers: $A_{(j,k)} = 1$ if (j, k) have the same seller and 0 otherwise; \mathbf{B} identifies third-party products collecting fees

$$\mathbf{B} = \begin{cases} 1 & \text{for } (j, k) : j \in \mathcal{J}_{SBA}, k \in \mathcal{J}_{3P} \\ 0 & \text{otherwise} \end{cases};$$

$\mathbf{\Omega}$ is a matrix of share-price derivatives

$$\Omega_{(j,k)} = -\frac{\partial s_k}{\partial p_j};$$

and (\mathbf{u}, \mathbf{v}) measure the potential fee revenue from consumers switching to third-party products when prices rise.

3.2.4 Fee-setting

Next we consider optimal fee-setting.

Unit fees. The first order condition of equation 2 with respect to the loadings on a particular unit fee instrument τ_m corresponding to instrument u_m is

$$\sum_l u_m s_l(\mathbf{p}) + \sum_{k \in 1P} (p_{kt} - \hat{w}_{kt}) \frac{\partial s_k(\mathbf{p})}{\partial \tau_m^u} + \sum_{l \in 3P} \left(\tau_m^u u_{m,l} \frac{\partial s_l(\mathbf{p})}{\partial \tau_m^u} + v_l p_l \frac{\partial s_l(\mathbf{p})}{\partial \tau_m^u} + v_l s_l \frac{\partial p_l}{\partial \tau_m^u} \right) + \gamma^c \frac{\partial CS(\mathbf{p})}{\partial \tau_m^u} + \gamma^s \frac{\partial SS(\mathbf{p})}{\partial \tau_m^u} = 0.$$

As above, the platform trades-off higher revenues from higher fees (first term) against decreased revenues from lower quantities, accounting for cross-elasticities across 1P and 3P products (second and third terms). The key difference is that the impact of higher fees on quantities now depends on how fees are passed on to prices:

$$\frac{\partial s_j}{\partial u_m} = \sum_l \frac{\partial s_j(\mathbf{p})}{\partial p_l} \frac{\partial p_l}{\partial u_m}.$$

Stacking the above conditions across fee instruments and using matrix notation, optimal unit fee loadings are

$$\boldsymbol{\tau}^u = (\boldsymbol{\Omega}_u \mathbf{U})^{-1} \left(\mathbf{U}' s(\mathbf{p}) - (\mathbf{C} \odot \boldsymbol{\Omega}_u) (\mathbf{p} - \hat{\mathbf{w}}) - \boldsymbol{\Omega}_u (\mathbf{v} \odot \mathbf{p}) + \boldsymbol{\rho}_u (\mathbf{r} \odot s(\mathbf{p})) + \gamma \boldsymbol{\rho}_u \frac{\partial CS(\mathbf{p})}{\partial \mathbf{p}} + \gamma \boldsymbol{\rho}_u \frac{\partial SS(\mathbf{p})}{\partial \mathbf{p}} \right), \quad (4)$$

where \mathbf{U} is a $N^u \times J$ matrix that collects fee instruments; \mathbf{C} is a $N^u \times J$ matrix that identifies 1P products ($C_{jk} = 1$ if $j \in \mathcal{J}_{3P}$, $k \in \mathcal{J}_{SBA}$) and $\boldsymbol{\Omega}_u$ is a $N^u \times J$ matrix of demand derivatives with respect to changes in unit fees:

$$\boldsymbol{\Omega}_{u(j,m)} = \frac{\partial s_j}{\partial u_m} = \sum_l \frac{\partial s_j(\mathbf{p})}{\partial p_l} \frac{\partial p_l}{\partial u_m}.$$

Using the concept of multidimensional passthrough matrix in the style of [Weyl and Fabinger \(2013\)](#); [Adachi and Fabinger \(2020\)](#), this matrix can be computed as $\boldsymbol{\Omega}_u = \boldsymbol{\rho}_u \boldsymbol{\Omega}$, where $\boldsymbol{\Omega}$ is defined above and $\boldsymbol{\rho}_u$ is a $N^u \times J$ matrix measuring how prices of *all* products change when the loading on a given unit tax instrument m increases, $(\boldsymbol{\rho}_u)_{jm} = \frac{\partial p_j}{\partial u_m}$. $\boldsymbol{\rho}_u$ is a complex object that depends on the specific tax instrument, as well as the buyer and seller elasticities and cross-elasticities. I describe how I estimate $\boldsymbol{\rho}_u$ in section 5 below.

Referral fees. Through a similar process, I recover Amazon's referral fee first-order condition as:

$$\boldsymbol{\tau}^v = ([\boldsymbol{\Omega}_v \odot \mathbf{p} - \boldsymbol{\rho}_v \odot s(\mathbf{p})] \mathbf{V})^{-1} \left(\mathbf{V}' (s(\mathbf{p}) \odot \mathbf{p}) - (\mathbf{C} \odot \boldsymbol{\Omega}_v) (\mathbf{p} - \hat{\mathbf{w}}) - \boldsymbol{\Omega}_v \mathbf{u} + \gamma^c \boldsymbol{\rho}_v \frac{\partial CS(\mathbf{p})}{\partial \mathbf{p}} + \gamma^s \boldsymbol{\rho}_v \frac{\partial SS(\mathbf{p})}{\partial \mathbf{p}} \right), \quad (5)$$

where all matrices are defined as above. Again, pricing depends crucially on pass-through and cross-elasticities across products.

3.3 Third-Party Sellers

Third-party sellers, denoted by s , take the fees as given and set prices in order to maximize short-run profits

$$\begin{aligned}\Pi^{3P} &= \sum_{j \in \mathcal{J}_s} \left((1 - v_j) p_j - (c_j + u_j^l) \right) s_j(\mathbf{p}), \\ &= \sum_{j \in \mathcal{J}_s} (1 - v_j) (p_j - \hat{c}_j) s_j(\mathbf{p}),\end{aligned}$$

where $\hat{c}_j = \frac{c_j + u_j^l}{1 + v_j}$ denotes the “effective” marginal cost accounting for unit and ad-valorem fees; and \mathcal{J}_s denotes the products sold by seller s . The first order condition with respect to p_j is

$$(1 - v_j) s_j(\mathbf{p}) + \sum_{k \in \mathcal{J}_s} (1 - v_k) (p_k - \hat{c}_k) \frac{\partial s_k}{\partial p_j} = 0,$$

which shows that the seller trades-off increased revenues from higher prices (first term) against decreased sales, accounting for the possibility of consumers switching to other goods offered by the seller (second term).

Stacking these conditions into a matrix, we obtain the optimal 3P pricing policy

$$(1 - \mathbf{v}) \odot (\mathbf{p} - \hat{\mathbf{c}}) = (\mathbf{A} \odot \mathbf{\Omega})^{-1} ((1 - \mathbf{v}) \odot s(\mathbf{p})), \quad (6)$$

3.4 Wholesalers

Wholesalers take Amazon price-setting as given, and set a price w to maximize short-run profits

$$\Pi_t^m = \sum_{j \in \mathcal{J}_m} (w_j - c_j) s_j(\mathbf{p}),$$

where \mathcal{J}_m denotes the products sold by wholesaler m . The first order condition with respect to w_j is

$$0 = s_j(\mathbf{p}) + \sum_{k \in \mathcal{J}_M} (w_k - c_k) \frac{\partial s_k}{\partial w_j},$$

where

$$\frac{\partial s_k}{\partial w_j} = \sum_l \frac{\partial s_k}{\partial p_l} \frac{\partial p_l}{\partial w_j}.$$

Optimal wholesale mark-ups are then given by

$$\mathbf{w} - \mathbf{c} = (\mathbf{A} \odot \mathbf{\Omega} \boldsymbol{\rho}_w)^{-1} s(\mathbf{p}). \quad (7)$$

Wholesale prices are inversely proportional to (a) consumer elasticity of demand and (b) the platform’s pass-through. Since $\boldsymbol{\rho}_w$ depends on γ , this introduces an important interaction between wholesaler mark-ups and platform investment incentives. When γ is high, the platform aims to provide a better bundle for

consumers, passing through a smaller share of cost increases (i.e., ρ_w is low). Wholesalers internalize this and set higher mark-ups. As γ falls platform pass-through increases and wholesaler mark-ups fall.

3.5 Equilibrium

Definition 1. An equilibrium for a given subcategory k and week t is a set of retail prices $p_j \forall j \in k$, platform fee loadings τ^u, τ^r and wholesale prices $w_j \forall j \in k, j \in SbA$ that jointly satisfy (i) the 1P and 3P retail price-setting first-order conditions (equations (3) and (6)), (ii) the platform fee-setting FoC (equations (4) and (4)) and the wholesale price-setting first-order-condition (equation (7)) given the estimated subcategory-specific demand parameters $(\alpha^k, \zeta^k, \beta^k, \sigma^k)$ and platform investment incentives $(\gamma^{c,k}$ and $\gamma^{s,k})$.

4 Data

In order to estimate the model, I collect data from a variety of sources.

Sample Selection. I start by defining the sample to contain a randomly selected sample of 150 product subcategories that belong to the the Baby Products, Health and Household and Food root-categories that were exposed to a decline in Amazon fees in 2019 (which we describe in more detail below). In addition, I restrict the analysis to Aug-2018 - March-2020 where coverage of distribution methods and BuyBox prices improves; and sales ranks use a common definition.¹³

Product and Seller data. I then collect product-level information for all the products that belong to our sample of product subcategories from Keepa.com (hereafter Keepa). Keepa is a private online market intelligence service for Amazon buyers and sellers that has been scraping Amazon since 2011. Buyers use Keepa to track the price of desired items, while sellers use it to identify new product markets to enter or study competing products.

Keepa provides two types of information for each product. First, descriptive information including product codes (e.g., ASIN, UPC and EAN), product characteristics (e.g., brand, manufacturer, size), display information (e.g., product title and description on Amazon), and a product category tree (e.g., Automotive >...>Windshield Sunshades). Second, high-frequency time-series information containing (i) product-level sales rank, ratings and reviews as well as (ii) offer-level prices (including shipping), seller id and distribution method (SbA, FbA or FbM).¹⁴ Whenever there are multiple offers for the same product at the same time, Keepa records the BuyBox winner (i.e., the winner of the white box on the right side of the Amazon product detail page, where customers can add items to their cart). This winner is assigned by Amazon based on an an undisclosed algorithm that ranks sellers based on the price, seller ratings, and fulfillment methods.

¹³Amazon changed the “unit of analysis” for defining sales ranks in 2020, from variations to parent products which would affect the conversion to quantities.

¹⁴Keepa updates it’s data by repeatedly scraping Amazon’s product pages. Some time-series fields (e.g., Amazon prices and sales ranks) are updated several times per day but other fields critical to our analyses (e.g., the BuyBox price and seller identifiers) are updated only a few times per week.

Since more than 80% of Amazon sales go through the BuyBox, I assume that the BuyBox-winner captures all sales in the remainder of the analysis.¹⁵ To identify PL products, I collect a list of private label and exclusive brand of Amazon from TI Research and merge the brand names to Keepa. Last, to include as controls in demand estimation, I also collect Seller Rating and number of reviews for all the sellers in my sample.

In the end, this yields a high-frequency panel containing all the products offered within each category, the associated product sales rank, ratings and reviews; as well as the identity and characteristics of the BuyBox winning offer (which includes retail prices, distribution methods, seller identity, seller ratings and seller reviews). To harmonize time-periods across datasets, I then aggregate all high-frequency time-series to a daily frequency by taking the latest offer and Sales Rank for each product within each day.

Fee data. Next, in order to use as instruments in demand estimation and as targets in supply estimation, I merge fee information conditional on distribution method.¹⁶ For referral and fulfilment fees, I collect the history of fees directly from the Amazon website and implement the fee structures. Fees vary in complex ways within and across product categories, dimensions and weight. I replicate the fee policies at the product subcategory level.

Estimating sales quantities. I then convert daily sales ranks into sales quantities using estimates from AMZScout, a leading market intelligence provider for Amazon sellers. Consistent with economic research, these estimates assume that the relationship between sales quantities and sales ranks at the root category level follows a Power Law.¹⁷

Market definition. Last, I aggregate the data to the weekly level by adding daily sales and averaging end-of-day prices and other product characteristics.¹⁸ A key decision in the analysis is to define the market and compute market shares. I assume the market size is such that Amazon's market share equals the average between its e-commerce share and retail shares, as estimated by eMarketerPro which is roughly 20%. Increasing the market size leads to higher outside elasticities and therefore lower weights on consumer surplus. In future versions, I plan to include robustness analyses for alternate market size assumptions.

Summary statistics Table (1) presents summary statistics for all products in the Sunscreen subcategory, for which we will present results individually in the rest of the section. 18% of products are SbA and 45%

¹⁵Prime-eligible products are argued to have a higher chance of winning the BuyBox, *ceteris paribus*, which has been the subject of substantial criticism (e.g., [Mitchell and Sussman, 2019](#)).

¹⁶These data were initially gathered and implemented for a companion project, [Covarrubias et al. \(2022\)](#), which uses them to estimate pass-through across a large set of categories.

¹⁷[Chevalier and Goolsbee \(e.g., 2003\)](#); [Chevalier and Mayzlin \(e.g., 2006\)](#); [Brynjolfsson et al. \(e.g., 2006\)](#) study these relationships in books. [Chevalier and Goolsbee \(2003\)](#) use a combination of actual sales and sales rank data from one publisher, as well as experiments where they purchase individual items and track how the sales rank changes to argue that rank data fits a power law. [Brynjolfsson et al. \(2011\)](#) revisit this relationship using data for books collected in 2000 and 2008. They find that sales of high-ranked products have increased (i.e., the long tail has grown longer over time) and argue that, "while power laws are a good first approximation for the rank-sales relationship, the slope is not constant for all book ranks, becoming progressively steeper for more obscure books." In other words, splines fit the relationship between sales ranks and sales quantities better.

¹⁸The weekly timeline is chosen to roughly match the update frequency of BuyBox prices and selling methods.

Table 1: Summary statistics: Facial Sunscreen

This table shows the summary statistics across products in the “Facial Sunscreen” category. The first three columns report the share of products by distribution method. The next three report the distribution of prices and fees (conditional on the fees being relevant).

	SBA	FBA	prime	Prices (\$)	Ref fee (%)	Adv fee (\$)	FbA fee (\$)
count	2124	2124	2124	2124	1739	1739	956
mean	0.18	0.45	0.63	26.02	0.15	1.60	3.49
std	0.39	0.50	0.48	15.96	0.02	0.93	0.70
min	0.00	0.00	0.00	5.05	0.08	0.31	2.41
25%	0.00	0.00	0.00	14.40	0.15	0.88	3.19
50%	0.00	0.00	1.00	19.99	0.15	1.30	3.19
75%	0.00	1.00	1.00	36.39	0.15	2.22	3.28
max	1.00	1.00	1.00	73.60	0.18	4.54	5.47

of products are FbA. The remainder is captured by FbM products. The median price for a cheese is \$20. The median ad-valorem fee is 15% while the lowest is 8%. The median advertising fee is \$1.30, while the average unit fulfillment fee (for FbA products) is 3.50.

5 Estimation

Given a market dataset, I estimate the model in three steps.

5.1 Step 1: Assign Products to Nests

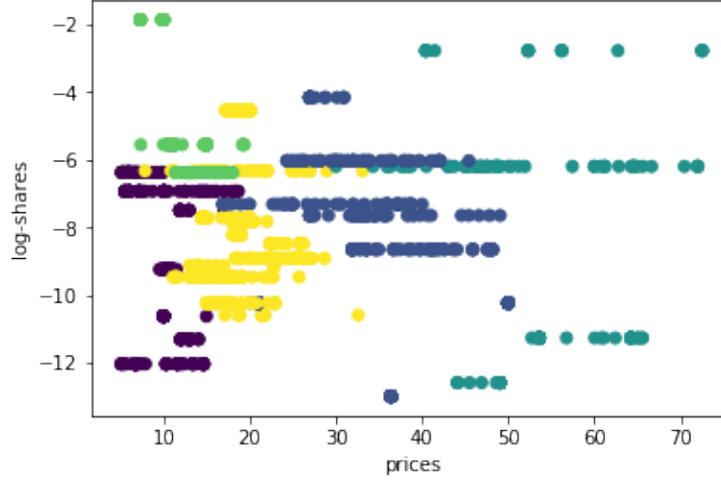
Approach. One of the main criticisms of the nested logit model is that nests must be set ex ante, often based on researcher discretion. This is problematic, first, because the nesting structure may not be obvious ex-ante and, second, because this approach is not scalable. To circumvent both of these issues, I follow [Almagro and Manresa \(2021\)](#) and recover the nest structure from the data.¹⁹

Practically, this involves two steps. First, I regress endogenous variables on instruments z (and included variables) to obtain \hat{x} . Second, I apply K-means clustering on the set of (residualized) product-specific moments $h_j = (\log P_j, \hat{x}_j')$, where $\bar{z}_j = \frac{1}{T} \sum_{t=1}^T z_{jt}$ denote means of z_{jt} . Since product fixed effects are not informative for K-means clustering, I exclude them from the analysis. Instead, I include a wide range of product characteristics including dimensions and weight as external moments in the clustering. Depending on the number of groups G , the K-means algorithm delivers different product partitions. I choose the number of nests that maximizes the Silhouette Score (a common proxy in the Machine Learning literature).

I believe this methodology is particularly appealing in our setting because (a) it is easily scalable over the hundreds of categories in our sample and (b) it can potentially be extended to include external measurement of types based on unstructured data that is widely available online (including, for example, textual data in

¹⁹[Almagro and Manresa \(2021\)](#) extend the Grouped Fixed Effects estimator of [Bonhomme et al. \(2019\)](#) to the case of Nested Logit models. In particular, they show that the nested logit model satisfies the assumptions of the Grouped can be factored into low-dimensional vectors analogous to grouped fixed effects; and that the same data used in demand estimation can be used to construct informative moments that map observables – namely, log-market shares and independent variables x_{jt} – to nests $g(j)$.

Figure 4: Sample Clustering Results: Facial Sunscreen



product titles and descriptions).

Results. Figure 4 shows the results of K-means clustering for the Facial Sunscreen category. As shown, the recovered nests follow rich structures that primarily on prices and market shares. This is consistent with intuition, if consumers search products primarily based on prices and sales rank.

5.2 Step 2: Estimate demand parameters, taking nests as given

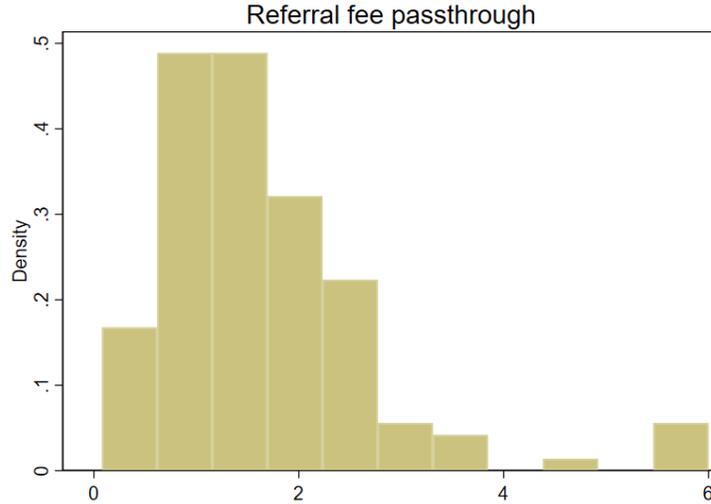
Approach. Next, I estimate demand parameters taking the nests as given. Inverting the demand system in equation X, we obtain the traditional estimating equation for the Nested Logit model

$$\ln s_{jt}^k - \ln s_{0t}^k = \alpha_t^k p_{jt} + \zeta^k 1\{\text{Prime}_{jt}\} + x_{j(s)t} \beta^k - \sigma^k \ln \left(s_{j|gt}^k \right) + \mu_j^k + \mu_t^k + \xi_{jt}, \quad (8)$$

where s_{jt}^k denotes the market share of product j in subcategory k at time t , s_{0t}^k denotes the outside good share and $s_{j|gt}^k$ denotes the share of product j within a group of products g . α^k measures the consumer price sensitivity in subcategory k . ζ^k measures consumer preferences for Prime fulfillment – interpreted as a bundle of services including 2-day shipping and Amazon’s return policy, for example. $x_{j(s)t}$ is a $1 \times K$ vector of additional product characteristics for product j in market t , which may depend on the identity of the seller s . μ_j denotes product fixed effects to control for the persistent component of unobserved quality (Nevo, 2001); and μ_t denotes product and time fixed effects which control for aggregate trends in the demand.

ξ_{jt} denotes unobservable month-specific deviations in product demand which, as pointed out by Berry (1994), are correlated with prices p_{jt} and, in our case, with Prime distribution. This creates an endogeneity problem. For example, demand for a Santa Claus costume may increase relative to that of a Princess costume around Christmas in ways that cannot be captured by observable x_{jt} characteristics. The seller will respond to the increase in demand by setting higher prices and/or using Prime distribution, which induces

Figure 5: *Distribution of referral fee passthrough*

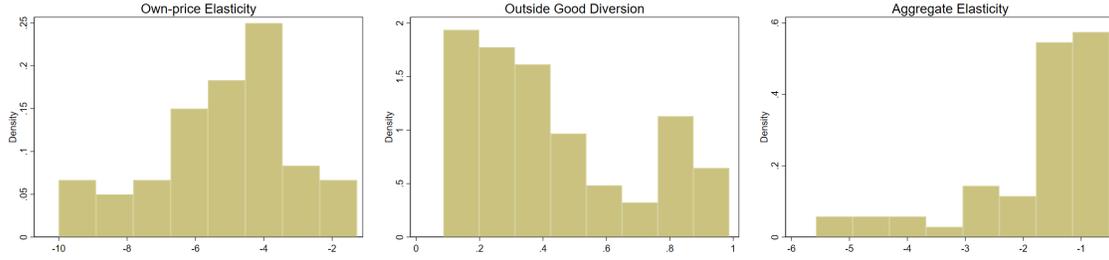


a correlation between sales, prices and distribution methods. Identification requires instruments z_{jt} that are correlated with prices and Prime eligibility but uncorrelated with unobserved product demand shocks so that $E[\xi_{jt}|z_{jt}] = 0$.

In order to instrument for prices, I exploit a natural experiment that occurred in 2019 where Amazon decreased referral fees from 15% to 8% on all third-party products that belong to the Baby, Health and Household and Food and Beverage root categories and have a price below \$10, while keeping referral fees for products with a price above \$10 fixed at 15%. We choose this experiment because it provides within-subcategory heterogeneity and therefore can be used in addition to product and time fixed effects. This instrument is a valid instrument because fees affect effective marginal costs, yet are set in advance, across a wide range of categories and without knowledge of individual product demand shocks. While there is a long history of using fees (or, really, government taxes) as instruments (e.g., [Conlon and Rao \(2015\)](#)), Amazon fees have the unique feature of being widely scalable across product categories. As a validation of the first stage, figure 5 presents the distribution of estimated pass-through across product subcategories. The median t-stat across categories is 9.2, and the median F-stat is 58.

I also instrument for Prime eligibility using a full set of third-party seller fixed effects, as a proxy for heterogeneous fulfillment and inventory costs that induce different preferences for Prime fulfillment across sellers. Sellers with high own-fulfillment costs (e.g., those without a warehouse or fulfillment operation) will prefer FbA, while sellers with low fulfillment costs (e.g., those with an operating fulfillment and warehousing network, perhaps for direct distribution) will prefer FbM. These instruments are valid as long as seller identity affects demand only by affecting Prime, after controlling for product and time fixed effects. The exogeneity restriction would be violated if buyers have preferences across sellers beyond Prime. The only observable information about sellers on the platform are seller ratings and reviews, so I include those as controls in the estimation.

Figure 6: *Distribution of estimated demand elasticities*



Results. Table 2 shows the estimated demand parameters. Panel (a) shows results for the Facial sunscreen category while Panel (b) shows the average parameters across all categories. All columns include product fixed effects. The first column estimates the model using OLS. As shown, the disutility in price is very low, and the coefficient on Prime gains is also very low (especially on Panel b). The second column instruments prices with referral fees but treats Prime as an exogenous parameter. As shown, the price coefficient increases drastically and so does the value of Prime. The next column instruments for Prime using seller fixed effects. Prime coefficients fall slightly, consistent with expectation. Column 4 repeats the estimation using the method of Gandhi et al. (2020) to address concerns of zeroes of demand. As shown, results remains stable. Column 5 allows for flexible nest correlation parameters across nests. The average within-nest correlation parameter drops to .054. Last, column 6 adds time fixed effects to arrive at our tightest specification, which we use in our supply analyses. As shown, all estimates remain largely stable. According to this specification, Prime increases utility by 0.32, which translates to approximately \$1.5 USD.

Last, figure (6) plots the distribution of weighted average own-price elasticities, outside good diversion ratios and aggregate elasticities. As shown, own-price elasticities are high with a median of -4. Outside good diversion ratios — which measure the portion of consumers that leave the platform rather than switch to an inside product when prices rise — are low, however, with a median of 30%. This implies that few consumers leave the platform when prices rise, so Amazon faces a fairly inelastic category level aggregate elasticity of between -1 and -1.3.

5.3 Step 3: Estimate supply parameters, taking demand parameters as given

Approach. In the last step, I estimate supply parameters taking the demand structure as given.

The intuition is straightforward: a short-run maximizing platform facing aggregate demands with an elasticity of approximately -1 would set very high mark-ups and very high fees (in our estimations, this translates to approximately 40%). In practice, Amazon sets much lower fees of approximately 20%. I use the wedge between observed and short-run profit maximizing fees to pin down the platform investment incentives. Specifically, the level of the wedge pins down the level of platform investment incentives, while the allocation of fees across instruments (which have different incidence on buyers and sellers) pins down the relative weights across participants.

To implement this, I start by mapping the real-world fee structure into matrices U, V . In particular, I endow the platform with three sets of instruments: one ad-valorem instrument that defines referral (i.e.,

Table 2: Estimated Demand Parameters

This table shows the estimated demand parameters for selected categories, as we progressively add fixed effects and instruments. Prime is an indicator equal to one when the product is distributed under the Prime program. σ reports the average within nest correlation parameter (which varies across nests where noted). The remaining parameters are standard.

Panel (a): Facial Sunscreen

	(1)	(2)	(3)	(4)	(5)	(6)
prices	-0.02	-0.15	-0.12	-0.11	-0.11	-0.11
prime	0.05	0.10	0.08	0.08	0.07	0.08
log(rating)	-3.32	0.02	0.03	0.02	0.03	0.02
log(sell. rating)	-0.29	0.01	0.02	0.01	0.01	0.01
log(# sell. reviews)	0.06	0.04	0.04	0.04	0.04	0.02
$\bar{\sigma}$	0.50	0.85	0.60	0.60	0.56	0.33
Obs.	1836	1836	1836	1836	1836	1836
Method	OLS	IVGMM	IVGMM	GLS	IVGMM	IVGMM
Prod FE	Y	Y	Y	Y	Y	Y
Seller FE Ins	N	N	Y	Y	Y	Y
Nest params	N	N	N	N	Y	Y
Time FE	N	N	N	N	N	Y

Panel (b): Average of All categories

	(1)	(2)	(3)	(4)	(5)	(6)
prices	-0.02	-0.24	-0.21	-0.21	-0.22	-0.22
prime	-0.14	0.31	0.28	0.28	0.21	0.32
log(rating)	-1.14	0.07	0.05	0.05	0.02	0.02
log(sell. rating)	-0.10	0.04	0.02	0.02	0.01	0.02
log(# sell. reviews)	-0.02	0.06	0.05	0.04	0.02	0.03
$\bar{\sigma}$	0.87	0.80	0.81	0.81	0.66	0.54
Obs.	19038	19038	19038	19038	19038	19038
Method	OLS	IVGMM	IVGMM	GLS	IVGMM	IVGMM
Prod FE	Y	Y	Y	Y	Y	Y
Seller FE Ins	N	N	Y	Y	Y	Y
Nest params	N	N	N	N	Y	Y
Time FE	N	N	N	N	N	Y

selling and matching) fees; and two unit fee instruments for fulfillment and advertising fees, respectively.²⁰ I initialize these vectors to (roughly) match the structure of fees observed in reality, at the corresponding week for which the market is defined. For referral fees, Amazon charges a 15% ad-valorem referral fee for products with a price above \$10 and an 8% fee for products below \$10 (in the subcategories we study). \mathbf{V} then includes a single vector equal to 0 for first-party products, 0.15 for third-party products with a price above \$10, and 0.08 for third-party products with a price of 0.08. During the model estimation, I hold $\tau^v = 1$ to recover the right fees. In counter-factuals, I hold \mathbf{V} fixed and allow the platform to adjust τ^v .²¹ For advertising, I assume that all 3P sellers pay a constant rate of their revenues in advertising, estimated as the ratio of total Amazon advertising revenues to 3P sales. The vector, then, is initialized to approximately 5% of the selling price (in dollars). Again, we hold this fee fixed when estimating the model and allow the platform to adjust $\tau^{u,1}$ in counterfactuals. Last, for fulfillment, I assume that the platform charges a common mark-up over fulfillment fees across all FbA products. The associated fee vector is then initialized to equal total fulfillment fees and the associated equilibrium mark-up rate is estimated with the rest of the parameters of the supply model.

Next, I estimate supply parameters by solving for the equilibrium mark-ups and platform weights that rationalize the observed prices, referral and advertising fees while jointly satisfying Amazon's first-order conditions; as well as wholesaler and third-party price-setting FoCs.²² I use a nested search algorithm with retail and wholesale prices at the narrowest level, followed by referral fees and fulfillment fees.

As described above, many of the first-order conditions of the problem depend on multidimensional passthrough matrices ρ_r, ρ_t, ρ_w . These are complex objects that depend on the elasticity, cross-elasticity and curvature of demand. They can easily be estimated through simulation. However, given that there are hundreds of products and that solving the supply model requires repeatedly measuring pass-through to compute first-order conditions, a simulation-based approach is prohibitively slow. To speed up calculations, I instead compute pass-through analytically. Let \mathbf{Z} be a matrix that collects the price-setting first-order conditions

$$\mathbf{Z} = \begin{cases} (\mathbf{A} \odot \boldsymbol{\Omega})(\mathbf{p} - \hat{\mathbf{c}}) + s(\mathbf{p}) & \text{if 3P} \\ (\mathbf{A} \odot \boldsymbol{\Omega})(\mathbf{p} - \hat{\mathbf{w}}) + s(\mathbf{p}) - (\mathbf{B} \odot \boldsymbol{\Omega})(r\mathbf{p} - \mathbf{u}) + \gamma \frac{\partial \mathbf{C} \mathbf{S}_t}{\partial \mathbf{p}} & \text{if SbA} \end{cases}$$

Using the implicit function theorem, the pass-through rate matrix can be derived as

$$\frac{\partial \mathbf{p}}{\partial \mathbf{u}_m} = - \left(\frac{\partial \mathbf{Z}}{\partial \mathbf{p}} \right)^{-1} \left(\frac{\partial \mathbf{Z}}{\partial \mathbf{u}_m} \right),$$

²⁰In reality, ad-valorem fees include a small closing unit fee, fulfillment fees include a quasi-fixed storage cost and advertising fees depend on the nature of advertising.

²¹I focus on explicit unit and ad valorem fees in this paper. However, as described by [Weyl and Fabinger \(2013\)](#) and [Adachi and Fabinger \(2020\)](#), many interventions ranging from exogenous competition to selling advantages enter third-party seller's problem as a mixture of unit and ad-valorem taxation. They could, therefore, be easily incorporated into our framework.

²²This estimation methodology assumes that Amazon jointly maximizes across all first-order conditions. This is a standard assumption, and a useful benchmark. It is likely plausible for prices, advertising and fulfillment fees which Amazon adjusts frequently. It may be less plausible for referral fees, which exhibit limited heterogeneity and have remained largely fixed for many years.

which depends on the specific tax instrument u_m (or v_m). The challenge, then, is to compute these matrices given a demand and supply structure.

Ultimately, supply estimation recovers five objects: (i) Amazon’s dynamic investment incentives; (ii) Amazon’s mark-up on FbA services; (iii) Amazon’s mark-up on 1P products; (iv) third-party mark-ups; and (v) wholesaler mark-ups. Using the estimated mark-ups, I then recover marginal and wholesale costs as well as Amazon’s fulfillment costs, which serve as inputs to counter-factuals.

Results. Table (3) provides an overview of the estimated supply and demand structure. The first column presents results for Facial Sunscreen. The next two columns present the mean and median value across our sample of subcategories. In the categories we study, roughly 20% of sales are 1P, 47% are sold via FbA and 33% are sold through FbM. The average Prime coefficient is 0.32 while the median is substantially lower. As described above, own-elasticities are high at approximately -5 but outside diversion ratios are low. This results in a relatively low aggregate elasticity.

The average estimated net fee rate charged by Amazon is 22%, composed of a 12% ad valorem fee and a 1.33 unit fee. This fee rate is substantially below that of a profit-maximizing platform which translates to relatively high investment incentives parameters of 1.04 for consumers and 0.4 for sellers. Given these incentives, we estimate that the average 1P mark-up is 37%. The average 3P mark-up is 34% and the average wholesale mark-up is 30%. Weighted average pass-through on referral and fulfillment fees is roughly equalized around 0.7.

6 Counter-factuals

Equipped with an estimated model, we can now perform a series of counterfactuals that cast light on Amazon’s strategy, as well as the welfare effects of proposed regulations. In particular, we consider the following four counterfactuals:

1. No investment incentives ($\gamma^j = 0$): in the first counter-factual, I simply solve the model assuming that investment incentives $\gamma^c = \gamma^s = 0$. This is useful to (i) quantify the extent to which dynamic investment incentives lead to lower prices and (ii) provide intuition behind the supply estimation approach for the model.
2. Structural separations (SS): The second counterfactual considers the welfare consequences of imposing structural separations on the platform. It is inspired by the “Ending Platforms Monopolies Act” which, if implemented, would ban hybrid platforms altogether and would force Amazon to divest portions of it’s business. In the analysis, I assume that the platform is broken up into a “reseller” that sets prices on first-party products, a “marketplace” that sets ad-valorem referral fees and a “logistics” company that sets unit fulfillment and advertising fees. Doing so eliminates gains/losses from internalization across business lines. The welfare consequences are ambiguous and depend on the platform’s investment incentives.

Table 3: Summary of Supply and Demand Structure

This table shows key estimated demand and supply parameters and equilibrium quantities for selected Amazon categories (first five columns) and the average across a sample of ten categories. All measures report the dollar-weighted average unless otherwise noted.

Parameter		Facial	All subcategories		
		Sunscreen	Mean	Median	
Demand	% of Sales	IP	38%	20%	20%
		FbA	40%	46%	47%
		FbM	22%	34%	33%
	Prime	Prime coeff	0.08	0.32	0.075
	Elasticities	Median ε_{own}	6.03	10.78	9.84
		ε_{own}	3.96	5.50	4.90
		θ	0.58	0.32	0.29
		Agg ε	1.88	1.30	1.17
	Pass-through	ρ_r	0.61	0.68	0.73
		ρ_u	1.01	0.81	0.71
Supply	Fees	Avg. ad val fee	0.22	0.12	0.12
		Avg. unit fee	0.65	1.70	1.33
		Total fee rate	0.24	0.23	0.22
	Inv. Incentives	γ^c	0.36	1.04	1.11
		γ^s	0.08	0.39	0.20
	Prices	Price	18.89	16.44	12.53
3P mark-up		0.31	0.34	0.30	
WH mark-up		0.53	0.30	0.22	
1P mark-up		0.39	0.37	0.35	
Other	Inside share	0.31	0.32	0.27	
	% mc < 0	0.04	0.10	0.03	

3. Ban reselling (ban 1P): The next counterfactual studies the welfare consequences of banning reselling. This policy was been progressively implemented in India starting in 2013, with the goal of supporting small third-party sellers.²³ I assume that all 1P products remain in the platform but transition to being offered under FbA. Amazon loses all price-setting capabilities and instead relies on the shared fee structures for monetization. This restricts the platform’s ability to use reselling to discipline seller market power.
4. Increase competition in Fulfillment (SFP): The last counterfactual considers the (forced) introduction of a “Seller Fulfilled Prime” program, which would require Amazon to give the Prime checkmark to any seller that can consistently meet pre-specified performance metrics. Such a program previously existed, but has been progressively closed by Amazon over the past few years. I assume that increased competition limits Amazon’s ability to charge a mark-up on fulfillment services effectively removing that instrument from the set of platform policy variables.

For each counter-factual and each product category in the sample, I first adjust the market structure as described above and then solve for the new equilibrium. The results measure the “short run” effects holding the number of buyers and sellers constant. In the long run, the number of buyers and sellers will adjust according to (a) buyer and seller entry elasticities and (b) the strength of network effects.

Facial Sunscreen. Table 4 presents results for the Facial Sunscreen category. The first column reports the baseline equilibrium quantities after solving the model (i.e., they are the same as those in Table 3). The remaining columns report results for each counter-factual. The top rows contain equilibrium quantities, while the bottom rows report changes in participant surplus.

The second column reports equilibrium objects and changes in welfare when we set $\gamma^j = 0$. As expected, removing investment incentives leads to a sharp increase in first-party mark-ups, referral and unit fees. The inside share of sales drops from 31% to 23%. Surplus declines for all participants except for Amazon. For sellers, the decline is driven by the increase in fees. For wholesalers, the decline is driven by fewer quantities and lower mark-ups, primarily because Amazon’s pass-through increases as investment incentives decline. This forces wholesalers to decrease their mark-up. For buyers, the decline is driven by higher prices across all distribution methods.

The third column reports equilibrium objects when imposing a structural separation. As expected, such a policy has differential effect across instruments: 1P mark-ups and referral fees fall while unit fees rise. This is likely explained by the fact that unit taxes have a higher incidence on consumers (Anderson et al., 2001), so a combined entity with higher buyer investment incentives will load more heavily on ad-valorem and 1P mark-ups. The net fee rate on 3P products increases from 24% to 29%, which leads to a decline in seller surplus. Welfare falls for the platform, buyers and sellers but increases for wholesalers.

The fourth column considers banning 1P sales. The platform responds by raising unit fees – particularly on FbA products – which now capture the vast majority of sales. The elimination of 1P offers restricts the platform from using reselling to discipline seller market power, which leads third-party mark-ups to rise and

²³See [here](#), for example.

Table 4: Counterfactual Results: Facial Sunscreen

This table shows the equilibrium fees, prices and welfare in the Facial Sunscreen category under a variety of counter-factual scenarios. The top rows present equilibrium objects. The bottom rows present changes in surplus, by participant. Changes in sellers/wholesaler surplus hold the identity of agents fixed even as the distribution method changes.

		Base	$\gamma^j = 0$	Struc. Sep	Ban 1P	SFP
Distn	% 1P	0.38	0.35	0.47	0	0.37
	% FbA	0.40	0.41	0.36	0.77	0.42
Fees	Avg. ad val fee	0.22	0.33	0.20	0.18	0.24
	Avg. unit fee	0.65	0.87	1.83	2.93	0.00
	Total fee rate	0.24	0.35	0.29	0.35	0.24
Share	AMZ share	0.31	0.23	0.28	0.31	0.30
	3P mark-up	0.31	0.31	0.31	0.53	0.32
	WH mark-up	0.53	0.40	0.61		0.53
	1P mark-up	0.39	0.53	0.28		0.38
Δ Surplus	Consumers		-3.03	-0.62	-0.08	0.09
	Sellers		-0.07	-0.04	0.23	0.01
	Wholesalers		-0.08	0.08	-0.24	-0.01
	Amazon		0.08	-0.04	0.03	-0.01
	Total		-3.10	-0.62	-0.06	0.08

increases seller surplus. This is consistent with the stated policy objective in India. Buyer and wholesaler welfare falls slightly, but the effects are in general very small. The former due to lower price discrimination on key products. The latter due to increased competition against third parties. In a static sense, such a policy actually increases the platform’s surplus. In a dynamic sense, however, this leaves consumers and wholesalers worse off – which may explain why the platform continues to resell products.

The last column restricts the platform from charging a mark-up on fulfillment services. The platform responds by raising referral fees, which partially offsets the gains from the intervention. In the end, consumers benefit slightly while platform surplus remains largely stable.

Summary of Regulatory Counter-factuals To conclude, table 5 shows the average counter-factual welfare implications across all product subcategories in our sample. The results are broadly consistent with those above, with interventions having fundamentally different effects across participants. Eliminating investment incentives leads to an increase in platform surplus, offset by a fall in buyer, seller and wholesaler surplus. Imposing structural separations leads to an increase in fees, which benefits wholesalers at the expense of buyers and sellers. Banning reselling, by contrast, benefits third-party sellers at the expense of wholesalers although the welfare consequences are small. Last, increasing competition in fulfillment leads to a slight increase in buyer welfare at the expense of platform surplus.

7 Conclusion

This paper develops and estimates a structural model of the Amazon platform, and uses it to study the “short-run” implications of regulatory interventions. Theoretically, it shows that Amazon’s business model,

Table 5: Average Counterfactual Results

This table shows the average change in participant surplus across all categories in our sample under multiple counter-factual scenarios. Changes in sellers/wholesaler surplus hold the identity of agents fixed even as the distribution method changes.

	$\gamma^j = 0$	Struc. Sep	Ban 1P	Comp. Fulf.
Consumers	-1.98	-0.19	-0.03	0.15
Sellers	-0.11	-0.06	0.11	0.00
Wholesalers	-0.08	0.04	-0.14	0.00
Amazon	0.20	0.00	0.04	-0.07
Total	-1.97	-0.21	-0.01	0.08

fee policies and market power have important implications for the welfare consequences of regulation. This points regulators towards platform- or market-specific interventions that are robust to the endogenous response of platform fees and business models. Empirically, it shows that interventions that eliminate either the Prime program or product variety are likely to decrease welfare. This points regulators towards interventions that preserve Prime and product variety but increase competition.

These insights are based on selected categories and depend crucially on some estimation assumptions. In future versions of this paper, I hope to (a) scale up the analyses to hundreds of categories in order to perform richer cross-sectional analyses; (b) explore alternate fee structures such as advertising and steering; and (c) consider alternate estimation assumptions around the size of the market and Amazon’s fee-setting behavior.

In the long run, there is further research needed to understand the determinants between business models, as well as the role of entry and competition for equilibrium outcomes. I pursue some of these in companion papers. [Gutierrez \(2022a\)](#) studies the determinants of reselling vs. marketplace intermediation. [Gutierrez \(2022b\)](#) extends the model to include buyer and seller entry decisions; and uses a reduced form Differences-in-Differences strategy to quantify the welfare consequences of private label product introduction.

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