

Fulfillment by Amazon and Prime: Who Benefits and How?

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Abstract

Amazon is known for its Prime shipping program, which offers fast, often two-day, delivery on eligible products. However, for most third-party sellers on the platform, obtaining Prime eligibility effectively requires using Amazon's fulfillment service, Fulfillment by Amazon (FBA). The FTC has sued Amazon over this arrangement, arguing that tying Prime eligibility to FBA imposes additional costs on third-party sellers that rely on Amazon to reach consumers. But greater FBA adoption may generate efficiencies through economies of scale and the elimination of double marginalization between Amazon's referral fee and FBA fee. To quantify the net effect, I build and estimate a model of consumer demand, sellers' pricing and fulfillment choice, and Amazon's joint setting of referral and FBA fees, and use it to evaluate counterfactual policies motivated by current policy discussions. I find that allowing sellers with sufficiently fast self-fulfillment to qualify for Prime without using FBA, as under Seller Fulfilled Prime, is close to welfare neutral for consumers while raising profits for third-party sellers. In contrast, banning Amazon from displaying the Prime badge altogether makes both consumers and sellers worse off.

JEL Codes: L42, L81, L13

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1 Introduction

Amazon’s Prime badge on product listings promises fast, free delivery on eligible products. For third-party sellers, however, Prime eligibility comes with a condition. Amazon effectively ties the Prime badge to its fulfillment service, Fulfillment by Amazon (FBA): a seller’s listings display the badge only if the seller pays Amazon to store and ship its products.¹ In September 2023, the Federal Trade Commission (FTC) sued Amazon, alleging that it maintains its monopoly power through a set of anticompetitive practices (Federal Trade Commission, 2023). One of the FTC’s allegations is that the tie coerces sellers into using FBA. According to the FTC, the tie adds to fees that already absorb nearly half of a typical FBA seller’s revenue, and sellers pass these fees through to consumers as higher prices.

The tie links a demand shifter, the Prime badge, to an input that Amazon offers to third-party sellers, its fulfillment service. Because consumers value the badge, a seller’s fulfillment choice is also a choice about whether to use FBA to qualify for Prime. This link can harm sellers and consumers even within Amazon’s marketplace. Sellers that could fulfill orders more cheaply themselves must still use FBA to obtain the badge. The tie also worsens sellers’ outside option to FBA, which can allow Amazon to raise its fees. Both raise sellers’ costs, and sellers may pass part of the increase through to consumers as higher prices.

At the same time, the tie can generate efficiencies. Because it steers more sellers into FBA, it raises the volume that Amazon fulfills. The first efficiency comes from economies of scale. Houde et al. (2023) find substantial economies of scale and density in Amazon’s fulfillment network, suggesting that higher FBA volume lowers Amazon’s per-unit fulfillment cost, and part of this saving can be passed through to FBA fees and retail prices. The second efficiency comes from fee coordination. A seller that fulfills its own orders pays a logistics provider whose price does not account for Amazon’s referral revenue. A seller that uses FBA pays both charges to Amazon. A higher FBA fee raises the seller’s price and lowers the referral revenue Amazon earns on the product. Amazon internalizes this effect, so it has an incentive to keep the FBA fee low and to earn its margin through the ad valorem referral fee. Pairing a low per-unit fee with a revenue share mitigates double marginalization (Anderson et al., 2023; Shy and Wang, 2011). By moving more sales into FBA, the tie extends this coordinated fee structure to more transactions. Consistent with this logic, FBA fees in my data are below Amazon’s estimated marginal fulfillment

¹Seller Fulfilled Prime (SFP), introduced in 2015, allows sellers that fulfill their own orders to display the Prime badge. Amazon paused new enrollment in SFP from 2019 until August 2023. To qualify, a seller must complete a trial period and meet stringent delivery-performance requirements. See Section 2 for details.

cost. The net effect of the tie is therefore an empirical question.

To quantify how linking the Prime badge with FBA usage shapes sellers' fulfillment choices and prices as well as Amazon's fees, and through them consumer welfare and third-party seller surplus, I build a model of consumer demand, sellers' pricing and fulfillment choices, and Amazon's fee setting. First, Amazon sets the referral and FBA fees to maximize an objective with four components: fee revenue from third-party sellers, profit from its own first-party sales, the total cost of operating its fulfillment service, and a weighted sum of seller and consumer surplus as a proxy for two sided incentives. I allow the cost of fulfilling FBA orders to exhibit economies of scale. In setting fees, Amazon anticipates sellers' responses under the rule that only products fulfilled via FBA are Prime eligible. Observing the fees, sellers then choose prices and fulfillment methods for their products. Finally, consumers make purchase decisions based on price, Prime eligibility, and product characteristics. The model thus captures both the costs the tie can impose on sellers and the efficiencies that greater FBA adoption can generate.

I estimate the model using a monthly panel from Keepa.com, which tracks Amazon product listings and seller offers over time. The sample covers facial sunscreen and laptops over 39 months, from December 2020 to February 2024, and includes 833 sunscreen products and 1,693 laptops. For each product, I observe sales rank, ratings, reviews, and characteristics such as brand and size. For each offer, I observe the seller, the listing price including shipping, the fulfillment method, and Prime status. I supplement these data with historical referral and FBA fees and shipping times collected directly from Amazon. As in most studies of online retail, exact quantities sold are not observed. Amazon does, however, display a coarse count of recent purchases on many listings (e.g., "20K+ bought in past month"), which Keepa records over time. Following the literature that infers quantities from sales rank (Chevalier and Goolsbee, 2003; Brynjolfsson et al., 2011; He and Hollenbeck, 2020), I use these counts to estimate the relationship between sales rank and quantity sold, and apply it to the full sample.

I estimate the model in three steps. First, I estimate a random-coefficients logit demand model (Pakes et al., 1995) in which utility depends on price, Prime eligibility, and delivery speed. Sellers choose both prices and, through their fulfillment method, Prime status, so I instrument for both. The instruments include cost shifters such as each product's FBA fee, which I compute from Amazon's fee schedule and the product's package dimensions. Second, I recover sellers' marginal costs by inverting their pricing first-order conditions. For FBA sellers, the computed FBA fee separates fulfillment cost from production cost. For FBM sellers, I predict production cost from a model estimated on FBA sellers. I also predict FBA sellers' costs of self-fulfillment from those of FBM sellers, capped at

USPS retail rates. Third, I recover the returns to scale in Amazon's fulfillment cost and the weights Amazon places on seller and consumer surplus from the first-order conditions of its fee-setting problem, assuming that observed fees are the optimal levels. Holding delivery speed fixed, consumers are willing to pay \$0.86 for the Prime badge on a sunscreen product and \$35 on a laptop, about 3% and 5.5% of the average price.

I use the estimated model to evaluate two counterfactual policies by quantifying the net effect of the Prime-FBA tying arrangement. The first expands Seller Fulfilled Prime (SFP), an existing program with low take-up: only 1-3% of offers in my data use it. In the counterfactual, any seller whose own delivery is sufficiently fast qualifies for the Prime badge automatically. The second removes the badge altogether but keeps delivery times visible to consumers. This eliminates Amazon's ability to steer demand through the badge, as opposed to through delivery speed itself. Comparing the two separates the effect of tying the badge to FBA from the role of the badge itself. The welfare effects of both policies depend on how the estimated badge premium is interpreted. Because I control for delivery speed, the premium captures demand beyond faster delivery. One important distinction to draw here is whether the estimated preference for Prime in the demand model reflects true utility or merely choice utility: whether consumers actually derive welfare from purchasing a Prime-listed product, controlling for shipping speed, or whether the badge raises demand only by making listings more salient. Controlling for shipping speed separates out the delivery-service component of Prime, but it remains unclear whether any true utility is left in the estimated preference. Therefore, in the counterfactual analysis I bound the actual effect on consumer surplus using two extreme cases: one in which the willingness to pay for Prime is entirely true utility (consumers genuinely benefit from purchasing a Prime-listed product), and one in which it is entirely choice utility (the badge influences consumers' choices but provides no additional benefit) (Allcott, 2013; Train, 2015).

Removing the badge lowers consumer surplus in both categories and under both interpretations of the badge premium. Combined across the two categories, consumer surplus falls by 11.6% if the premium is entirely true utility and by 3.3% if it is entirely choice utility. Consumers lose even when the badge provides no benefit, because prices rise and sellers leave FBA. Third-party sellers lose as well: their surplus falls by 12.9%, and about four-fifths of the loss comes from the demand the badge generated rather than from sellers' fulfillment responses. Expanding SFP, by contrast, is close to neutral for consumers in aggregate: consumer surplus rises by 0.1% if the premium is true utility and falls by 1.1% if it is choice utility. Seller surplus rises by 1.0%, mostly because sellers that used FBA only to obtain the badge switch to fulfilling orders themselves. Figure 1 summarizes

these effects.

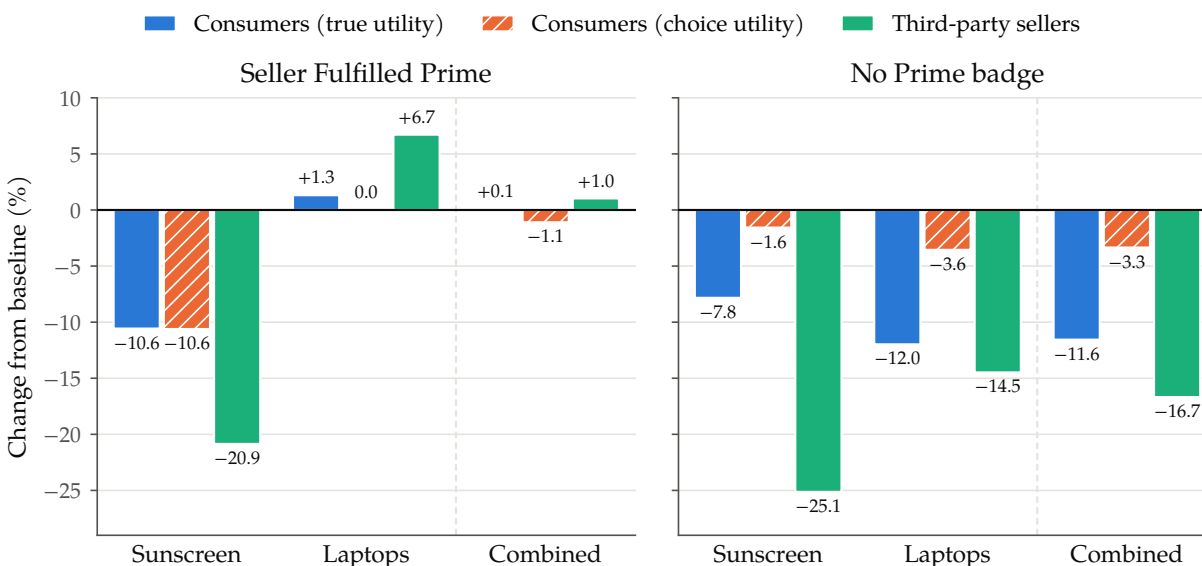


Figure 1: Who Benefits? Changes in Consumer and Seller Surplus

Notes: Percent change relative to the re-optimized baseline equilibrium, June 2023. Under the true-utility interpretation, consumer surplus is compared with the baseline consumer surplus; under the choice-utility interpretation, it is compared with the baseline with correction (Table 8). Seller surplus does not depend on the interpretation. *Combined* sums the two categories.

The aggregate SFP results mask opposite effects across the two categories, and the difference comes from how Amazon resets its fees. In sunscreen, Amazon responds to SFP by nearly doubling the referral fee, from 15.4% to 29.5%. The referral fee is the one charge Amazon collects from every seller, including newly eligible sellers that fulfill their own orders, so Amazon shifts its margin toward it. Prices rise by 5.9%, consumer surplus falls by 10.6% under either interpretation, and seller surplus falls by 21%. In laptops, Amazon instead lowers the referral fee, from 9.0% to 6.6%. Prices are essentially unchanged, consumer surplus rises by 1.3% under true utility and is unchanged under choice utility, and seller surplus rises by 6.7%. These results should not be surprising, as facial sunscreen is a much cheaper product while laptop is expensive and durable, so the difference in demand elasticity drives different incentives for Amazon. Breaking the link therefore does not by itself benefit sellers or consumers, and who benefits depends on how Amazon resets its fees in response.

These results inform remedies regarding Amazon's alleged anticompetitive behaviors. For example, in 2022, the European Commission accepted commitments from Amazon to set non-discriminatory criteria for Prime eligibility and to let Prime sellers choose their own carriers (European Commission, 2022). The SFP counterfactual approximates such

a remedy by assuming that sellers with shipping comparable to FBA qualify for Prime. The findings suggest that decoupling benefits sellers in aggregate and leaves consumers roughly unaffected. The effects, however, depend on how Amazon resets its fees: where Amazon shifts its margin to the referral fee, both consumers and sellers lose. The model captures Amazon’s incentive to make this shift, but not every force that shapes how Amazon sets its fees in practice. In practice, Amazon’s referral schedule rarely changes: most categories have a 15% referral rate, with exceptions such as computers and video game consoles at 8%. FBA fees, by contrast, have increased steadily over time. This pattern suggests that forces outside the model, such as competition from other online marketplaces, also affect how Amazon sets its referral rates. Removing the badge altogether is more a benchmark than a policy under discussion, but it shows more clearly how consumers’ preference for the badge, whether true or choice utility, affects equilibrium outcomes. Both consumers and third-party sellers are hurt when the badge is removed, even if the badge only shifts demand rather than providing true utility to consumers, suggesting an overall benefit of keeping the badge.

Estimation problem	Directly in the data	Challenge	Identified by
① Demand for Prime	Prices, Prime status, best sellers ranks, “100+ bought in past month” badges	Quantities not observed	Rank-to-quantity mapping: Pareto distribution (Chevalier and Goolsbee, 2003; Brynjolfsson et al., 2006), estimated from ranks and sales badges; Instruments: BLP-style (Pakes et al., 1995) + FBA-fee cost shifters
② Seller production & FBM fulfillment cost	FBA fee (known), prices, quantities, product characteristics	FBM sellers’ marginal cost combines production and fulfillment costs	Equilibrium restriction: marginal cost from inverting the pricing FOC; FBA production cost = marginal cost – known fee; projection of FBA production costs onto product characteristics separates FBM production and fulfillment costs
③ Counterfactual FBM cost for FBA products	Package dimensions, seller location	FBA products’ self-fulfillment cost never observed	Projection of FBM fulfillment costs from ② onto package and location; predicted out of sample
④ Amazon’s objective & cost function	Realized FBA/referral fees, category quantities	Amazon’s fulfillment costs and objective weights not observed	Equilibrium restriction: fee-setting FOCs as GMM moments + calibrated cost time trend

Related Literature

This paper adds to the emerging body of literature studying Amazon by connecting Amazon’s behavior as an online platform and a logistics service provider. The most closely related structural work is Gutierrez (2021), which studies the welfare consequences of

regulating Amazon’s dual role as a platform and a seller. Lee and Musolff (forthcoming) uses data on sales and Buy Box recommendations on Amazon Marketplace to estimate a model in which the platform’s recommendations guide consumer search and shape seller entry. They find that Amazon’s recommendations favor its own offers and that many consumers consider only the recommended offer. These studies abstract from the implications of Amazon also operating FBA and the potential efficiency gains from the extra pricing tool of FBA fees. Musolff (forthcoming) studies how third-party sellers on Amazon set prices and shows that repricing algorithms that periodically reset prices upward induce rivals to raise their prices as well, a form of tacit collusion. These studies abstract from the implications of Amazon also operating FBA and the potential efficiency gains from the extra pricing tool of FBA fees. Farronato et al. (2023) find that Amazon ranks its own brands higher in search results than observably similar products, and Raval (2024) shows that Amazon’s Buy Box algorithm favors both its retail arm and its fulfillment arm. The latter suggests that part of the demand advantage of Prime listings may reflect algorithmic steering toward FBA offers, which my choice-utility bound accounts for. Lai et al. (2022) uses a theoretical strategic competition model to demonstrate that FBA could mitigate price competition between Amazon and the third-party sellers, but does not consider the potential effect of Prime among other assumptions on the demand. Houde et al. (2023) studies the expansion of Amazon’s fulfillment network in states with different sales tax policies, demonstrating that the expansion has decreased the average shipping costs over time for Amazon, but it treats Amazon only as a retailer and not as a platform. On the theory side, a growing literature studies hybrid platforms that both host third-party sellers and sell on their own marketplaces (Hagiu and Wright, 2015b,a; Hagiu et al., 2020; Anderson and Bedre-Defolie, 2021; Hagiu et al., 2022), and Zhu and Liu (2018) document Amazon’s entry into product spaces previously served by third-party sellers. My model incorporates this dual role through Amazon’s first-party profit in its objective.

This paper also adds empirical evidence to the long thread of literature on vertical integration and its potential effects. It is established that revenue-sharing contracts, under which the upstream firm sells an input to downstream retailers (Amazon supplying fulfillment service to sellers) at a low unit price in exchange for a share of the revenue, mitigate double marginalization (e.g., Dana and Spier, 2001; Mortimer, 2008; Cachon and Lariviere, 2005). A related literature compares ad valorem and per-unit platform fees: proportional fees mitigate double marginalization (Shy and Wang, 2011) and can implement efficient price discrimination (Wang and Wright, 2017), paralleling the welfare advantage of ad valorem over unit taxes under imperfect competition (Anderson et al., 2001). The agency model of e-book retailing raises similar questions about revenue shar-

ing between a platform and its suppliers (Johnson, 2017; Foros et al., 2017). When regulators constrain one platform fee, platforms adjust others: after U.S. cities capped food delivery platforms' commissions, the platforms raised delivery fees for consumers (Li and Wang, 2025), a platform analog of the waterbed effect (Genakos and Valletti, 2011). With the theoretical predictions in mind, I study an empirical model to shed some light on the magnitude of such effects, especially on the prices and seller surplus.

This paper also adds to the existing empirical studies of vertical integration, as fulfillment service can be thought of as an input for sellers to complete transactions (Berto Villas-Boas, 2007; Bonnet and Dubois, 2010; Crawford et al., 2018). Hortaçsu and Syverson (2007) find that vertical integration in cement and ready-mixed concrete is associated with lower prices and higher productivity rather than foreclosure. Luco and Marshall (2020) show that eliminating double marginalization lowers the prices of a firm's integrated products but can raise the prices of its other products. This parallels a mechanism in my setting: because the referral fee applies to every seller in a category, sellers that do not use FBA pay it without benefiting from a lower FBA fee. In particular, by operating its own fulfillment network and offering FBA as a vertically integrated entity, Amazon might try to foreclose its competitors on the retail margin by making FBA expensive for the sellers, a form of raising rivals' costs (Salop and Scheffman, 1983). Because Amazon's objective in my model includes its first-party profit, the model captures this incentive.

The study of tying Prime eligibility to FBA usage is also related to the long history of antitrust studies of tying contracts, where sellers have to buy one good to get access to the other. In my setting, the Prime badge is the tying good, fulfillment is the tied good, and SFP corresponds to unbundling. The Chicago school argues that a monopolist gains nothing from tying, since it can extract its monopoly profit through the price of the tying good (Bowman, 1957; Posner, 1978). Although third-party sellers on Amazon are not technically paying for the Prime badge, the FBA fee effectively serves as its price. Because the referral fee rarely changes, the tie gives Amazon an additional instrument to monetize the badge. Consistent with this logic, Amazon raises the referral fee in the sunscreen category when SFP removes the tie. Leverage theories instead show that tying can extend market power into the tied market and foreclose rivals there (Kaysen and Turner, 1959; Whinston, 1990; Carlton and Waldman, 2002), which underlies the concern that the tie disadvantages competing fulfillment providers. Because my model takes sellers' self-fulfillment costs as given, I speak to the extraction and efficiency effects of the tie rather than to this foreclosure channel. Tying has also been studied in two-sided markets (Choi, 2010; Choi et al., 2017; Amelio and Jullien, 2012), and empirical work has quantified the effects of bundling and full-line forcing (Crawford and Yurukoglu, 2012; Ho et al., 2012).

The counterfactual results also provide some empirical evidence to the body of antitrust studies, especially given ongoing enforcement in the US and EU.

Finally, the Prime badge is a platform-provided quality certification, so this paper also relates to studies of certification and reputation on online marketplaces (Dranove and Jin, 2010). Elfenbein et al. (2015) and Hui et al. (2016) estimate the value of eBay’s seller badges, and Saeedi (2019) finds that removing eBay’s reputation mechanism lowers both seller profits and consumer surplus, consistent with my No Prime counterfactual. Because the Prime badge comes with fast delivery, whose value Fisher et al. (2019) document, I control for delivery times to separate the two. Methodologically, I estimate the weights in Amazon’s objective in the spirit of the conduct-parameter literature (Bresnahan, 1982; Genesove and Mullin, 1998; Miller and Weinberg, 2017), and I bound welfare following work on settings where choice and true utility differ (Allcott, 2013; Train, 2015).

Outline

The paper proceeds as follows. Section 2 discusses the institutional details, Section 3 describes the empirical model, Section 4 presents the data sources used to estimate the model, Section 5 contains the estimation methods and results, and Section 6 reports the counterfactual simulations. Section 7 concludes.

2 Institutional Background

2.1 Amazon’s Marketplace Structure and Fee Regime

Amazon operates as both a marketplace platform and a logistics provider, and charges third-party sellers a separate fee for each role. It also sells its own products on the marketplace as a first-party retailer. As a platform, it hosts millions of third-party merchants, who collectively account for more than 60% of sales in its store (Amazon, 2025). For this, it levies a *referral fee* on every sale—an ad valorem charge on order revenue that varies by product category, and in some categories by price, but applies universally regardless of how the product is fulfilled. As a logistics provider, it operates a vast fulfillment network that sellers can opt into. Those who do pay an additional per-unit *FBA fee* covering picking, packing, shipping, customer service, and returns. This dual role is central to the paper’s research question: Amazon effectively ties Prime badge eligibility to the use of its own fulfillment service, with the limited exception of Seller Fulfilled Prime discussed below, making a seller’s logistics decision inseparable from its competitive position on

the platform. Figure 2 illustrates this relationship.

Since its launch in 2006, FBA has become an essential part of the business model for a growing number of sellers, with more than 90% of third-party sellers using FBA for at least some of their products (Jungle Scout, 2020). Under FBA, sellers ship inventory to Amazon’s fulfillment centers in advance. Once an order is placed, Amazon ships it from its fulfillment network, and Prime members receive fast, typically two-day, delivery. FBA listings automatically qualify for the Prime badge. Enrollment in FBA is product-specific: a seller can use FBA for some of its products and fulfill the rest itself. Beyond the per-unit FBA fee, FBA users also incur *storage fees*—charged monthly per cubic foot of inventory held in Amazon’s warehouses—which accrue with the inventory a seller holds rather than with its sales. My model abstracts from storage fees and includes only the per-unit FBA fee. These storage fees, combined with the per-unit FBA fee structure that scales steeply with product weight and size, may help explain why 29% of sellers use both FBA and FBM (Jungle Scout, 2020), preferring FBM for heavier or slower-moving items.

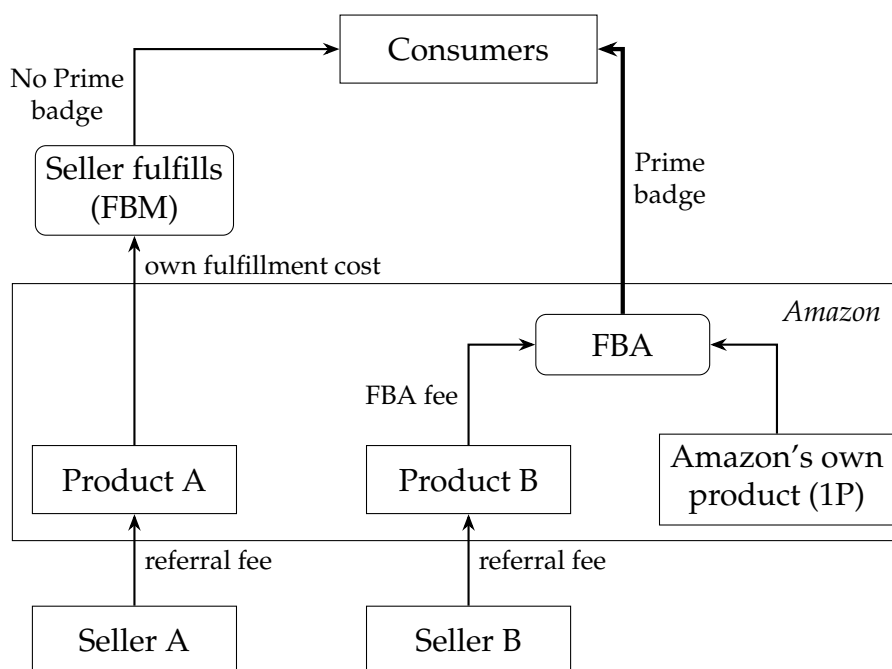


Figure 2: Fulfillment Methods, Fees, and Prime Eligibility

Notes: Arrows trace the path from each product to consumers. Every third-party sale pays the referral fee. Sellers that use FBA also pay the per-unit FBA fee, and products fulfilled by FBA, including Amazon’s own, display the Prime badge. Sellers that fulfill orders themselves (FBM) bear their own fulfillment costs and do not display the badge. The figure abstracts from Seller Fulfilled Prime.

Prime eligibility matters to sellers for reasons beyond consumer preference. Amazon’s search and recommendation algorithm reportedly favors Prime listings (Federal

Trade Commission, 2023), and Prime and FBA status are key inputs into winning the *Buy Box* (Raval, 2024)—the default “Add to Cart” offer that Amazon surfaces on a product page and which captures a disproportionate share of sales for any given product. Because of this algorithmic advantage, the value of Prime to a seller could extend beyond the delivery speed it highlights to consumers. For this reason, I treat both the algorithm effect of Prime and advertising as part of regular demand. The estimated Prime coefficient therefore captures both consumers’ valuation of the badge and the prominence the algorithm gives Prime listings. This is one reason I bound consumer welfare under both the true-utility and choice-utility interpretations of the badge in Section 6.

2.2 Seller Fulfilled Prime

Amazon does provide an alternative route to Prime eligibility for non-FBA sellers through the Seller Fulfilled Prime (SFP) program, though take-up among sellers has been nearly negligible in practice. SFP was first launched in 2015 and closed for new enrollment from 2019 to October 2023.² Obtaining and keeping SFP status involves three stages. First, sellers must hold a Professional selling account and check whether they are prequalified, based on having fulfilled a minimum number of packages and meeting baseline performance thresholds for late-shipment, valid-tracking, and cancellation rates. Second, prequalified sellers must complete a trial period, during which they must demonstrate that their fulfillment meets Amazon’s Prime delivery standards.³ Sellers who pass the trial are automatically enrolled in SFP and gain access to Prime branding for the products they fulfill themselves. Third, maintaining SFP status is an ongoing obligation: enrolled sellers must continuously satisfy Amazon’s performance requirements, and may lose their status if delivery targets are not met. To help manage this, Amazon allows SFP sellers to set daily caps on Prime orders so that volume does not exceed what they can reliably fulfill.

Even with the SFP program open, the demanding criteria make it very hard for sellers to qualify. In my data, less than 3% of offers are Prime without using FBA. Because new enrollment was closed during most of my sample period, these offers come mostly from sellers who enrolled before 2019. The SFP program therefore provides some flexi-

²Amazon had planned to charge SFP sellers a 2% fee on sales, but it dropped the fee when it reopened enrollment (Garland, 2023).

³When SFP was first launched, the trial required sellers to fulfill at least 200 “Prime trial” orders within up to 90 days, achieving at least 99% on-time shipment, less than 1% seller-initiated cancellations, and more than 95% of orders using Amazon Buy Shipping services—a program allowing sellers to purchase shipping labels directly from Amazon at discounted rates. When SFP reopened in 2023, the trial window was shortened to 30 days, with revised thresholds: at least 100 packages shipped, a 93.5% on-time delivery rate, 99% valid tracking rate, less than 0.5% seller-initiated cancellations, and minimum one-day and two-day delivery speeds as measured by Prime customer detail page views.

bility for sellers, but not enough to meaningfully break the tie between FBA usage and Prime eligibility. My SFP counterfactual in Section 6 instead grants the badge to any seller whose own delivery meets the two-day standard, abstracting from the trial and ongoing performance requirements.

2.3 Amazon’s Fulfillment Network

Since the 2000s, Amazon has invested heavily in expanding and improving its fulfillment network. Three types of facilities determine Amazon’s cost of delivery: fulfillment centers, sortation centers, and delivery stations (Houde et al., 2023). Fulfillment centers store products and pick, pack, and ship orders. Sortation centers, which Amazon began opening around 2014, sort packages by final destination and send them on for last-mile delivery. Before then, independent carriers such as UPS and FedEx picked up packed orders and moved them through their own sortation and delivery networks. Since 2014, many packages instead pass through Amazon’s sortation centers, and in 2018 Amazon began building its own last-mile capacity through its Delivery Service Partner program, further integrating these services. Amazon nonetheless still hands many packages to the U.S. Postal Service for final delivery. Houde et al. (2023) show that the expansion of this network substantially lowered Amazon’s average fulfillment cost and that order processing exhibits economies of scale. Higher order volume may also improve the rates Amazon obtains from carriers such as USPS. These forces motivate the economies of scale in Amazon’s fulfillment cost function in my model (Section 3).

3 Model

This section describes the model of consumers’ purchase decisions, sellers’ pricing and fulfillment choices, and Amazon’s fee setting. Consumers are indexed by i , products by j , markets by m , and periods by t . I assume each seller lists one product, so j also indexes sellers. I define a market as an Amazon product subcategory (e.g., “facial sunscreen” or “laptops”), and a period as a month. Let $\mathcal{J}_{mt}$ denote the set of all products offered for sale in market m in period t , across all sellers. I partition it into Amazon’s own products, $\mathcal{J}_{mt}^{1P}$, and third-party products, $\mathcal{J}_{mt}^{3P}$.

The game proceeds in three stages. In stage 1, Amazon sets the referral and FBA fees. In stage 2, third-party sellers simultaneously set prices and choose fulfillment methods, taking the fees as given. In stage 3, consumers make purchases. I solve the model by backward induction.

3.1 Consumer Demand

Consumer i 's utility from buying product j in market m in period t is given by

$$u_{ijmt} = \beta X_{jmt} - \alpha_i p_{jmt} + \beta_{Prime} Prime_{jmt} + \beta_{shipping} FastestDelivery_{jmt} + \xi_{jmt} + \varepsilon_{ijmt}. \quad (1)$$

X_{jmt} includes observable product characteristics such as ratings and the number of reviews. p_{jmt} is the total price paid by the buyer, equal to the listed price plus shipping cost, and the associated price coefficient is heterogeneous across consumers, $\alpha_i \sim \text{LogN}(\mu_\alpha, \sigma_\alpha^2)$, so that consumers differ in their price sensitivity. $Prime_{jmt}$ is an indicator for whether the listing carries the Prime badge. $FastestDelivery_{jmt}$ is the number of days of the fastest available delivery. ξ_{jmt} captures unobserved product quality. The utility of the outside option is normalized to $u_{i0mt} = \varepsilon_{i0mt}$, and the shocks ε_{ijmt} , including ε_{i0mt} , are i.i.d. Type I extreme value.

It is worth noting that β_{Prime} measures consumers' revealed preference for the Prime badge, which may conflate true utility from buying a Prime product, controlling for fastest delivery, with effects of the badge on choices that do not reflect true utility. That is, a consumer's observed choices are governed by *choice* utility, while consumer welfare is governed by *true* utility, and the two need not coincide when an attribute shapes demand without conferring a corresponding real benefit (Allcott, 2013; Train, 2015; Cao et al., 2024). I assume that controlling for actual delivery speed via $\beta_{shipping} FastestDelivery_{jmt}$ captures the true service-quality benefit of faster shipping, so that any residual preference for the badge captured in β_{Prime} does not reflect that channel. What remains may reflect real benefits of the badge, such as Amazon's handling of customer service and returns for FBA orders, or a perception-based effect, in which the badge makes listings more salient without a corresponding benefit. β_{Prime} may also capture algorithmic favoritism toward Prime listings (Raval, 2024), which operates on listing visibility rather than on consumer preferences. This channel cannot be separated from the behavioral channel with the data currently available, and like the perception-based effect, it falls under the choice-utility interpretation. This distinction does not affect demand estimation or sellers' choices, which depend only on choice utility, but it matters for measuring consumer welfare. Since I cannot determine how much of β_{Prime} reflects true rather than choice utility, I bound the change in consumer surplus in each counterfactual using two polar cases: one in which β_{Prime} is entirely true utility, and one in which it is entirely choice utility (Section 6).

Let $\delta_{jmt} \equiv \beta X_{jmt} + \beta_{Prime} Prime_{jmt} + \beta_{shipping} FastestDelivery_{jmt} + \xi_{jmt}$ denote product j 's mean utility in market m in period t , common to all consumers. Since the price coefficient α_i is consumer-specific, the price term $-\alpha_i p_{jmt}$ enters through $\mu_{ijmt} \equiv -\alpha_i p_{jmt}$ instead.

Normalizing the outside option's mean utility to $\delta_{0mt} = 0$ and integrating the Type I extreme value shock ε_{ijmt} out in closed form gives the market share of product j in market m in period t :

$$s_{jmt} = \int \frac{\exp(\delta_{jmt} + \mu_{ijmt})}{1 + \sum_{g \in \mathcal{J}_m} \exp(\delta_{gmt} + \mu_{igmt})} dF(\alpha_i), \quad (2)$$

where F is the lognormal distribution of α_i .

3.2 Sellers

For a given market and period, I drop the subscripts m and t for brevity. In each period, sellers observe Amazon's referral fee τ , the FBA fee f_j^{FBA} for their product, and their own cost of fulfilling orders themselves, f_j^{FBM} . Sellers then simultaneously choose a price and a fulfillment method for their products. The fulfillment choice determines Prime eligibility: enrolling in FBA automatically grants the product the Prime badge, while FBM listings do not qualify. In the benchmark model, I rule out SFP because SFP offers are extremely rare in the data (see Table ??), so $Prime_j = FBA_j$, where FBA_j indicates that product j is fulfilled through FBA. Seller j solves the following two problems and selects whichever yields the higher profit:

$$\pi_j^{FBA} = \max_{p_j} [(1 - \tau)p_j - c_j - f_j^{FBA}] D_j(p_j, Prime_j = 1; p_{-j}, Prime_{-j}), \quad (3)$$

$$\pi_j^{FBM} = \max_{p_j} [(1 - \tau)p_j - c_j - f_j^{FBM}] D_j(p_j, Prime_j = 0; p_{-j}, Prime_{-j}), \quad (4)$$

where c_j is the production cost of product j and $D_j(\cdot)$ is its demand, equal to market size times the market share in equation (?). The seller chooses FBA if and only if $\pi_j^{FBA} \geq \pi_j^{FBM}$, and sets the corresponding optimal price. Since the referral fee τ is common across sellers within a market and the FBA fee is set by Amazon's fee schedule based on product size and weight, heterogeneity in the fulfillment decision is driven by differences in FBM costs f_j^{FBM} and production costs c_j , as well as product characteristics.

3.3 Platform

In each period t , Amazon sets the referral fee τ_{mt} and the FBA fee schedule f_{mt}^{FBA} in each market to maximize its objective across markets, taking into account how these fees affect sellers' fulfillment choices and pricing. The fee schedule assigns each product a per-unit

fee f_{jmt}^{FBA} based on its size and weight.⁴ Because Amazon also sells its own products, I separate its first-party (1P) selling profit from the fee revenue it earns hosting third-party (3P) sellers, and subtract its fulfillment cost. To capture Amazon’s incentive as a two-sided platform—attracting both sellers and consumers—I augment this objective with a weighted sum of consumer surplus (CS) and seller surplus (SS), which I refer to as the two-sided incentives. Specifically, Amazon solves

$$\begin{aligned}
& \max_{\{\tau_{mt}, f_{mt}^{FBA}\}_{m=1}^M} \underbrace{\sum_{m=1}^M \sum_{j \in \mathcal{J}_{mt}^{1P}} D_{jmt} (p_{jmt} - c_{jmt})}_{\text{first-party selling profit}} \\
& + \underbrace{\sum_{m=1}^M \sum_{j \in \mathcal{J}_{mt}^{3P}} D_{jmt} (\tau_{mt} p_{jmt} + FBA_{jmt} f_{jmt}^{FBA})}_{\text{third-party fee revenue}} \\
& - \underbrace{\sum_{m=1}^M C_{mt} \left(\sum_{j \in \mathcal{J}_{mt}} FBA_{jmt} D_{jmt} \right)}_{\text{fulfillment cost}} \\
& + \underbrace{\theta^c \sum_{m=1}^M CS_{mt} + \theta^s \sum_{m=1}^M SS_{mt}}_{\text{two-sided incentives}}, \tag{5}
\end{aligned}$$

where prices p_{jmt} , fulfillment choices FBA_{jmt} , demand D_{jmt} , and surpluses CS_{mt} and SS_{mt} are the equilibrium outcomes of the seller stage given the fees.

The first line of the objective is Amazon’s profit from selling directly to consumers as a first-party seller. I assume Amazon values a dollar of first-party profit the same as a dollar of fee revenue from third-party sellers. The second line is the referral and FBA fee

⁴I assume Amazon observes each product’s package dimensions and weight, so its choice of the fee schedule f_{mt}^{FBA} determines the fee f_{jmt}^{FBA} of every product. In the seller problem, where the market and period subscripts are dropped, this fee is f_j^{FBA} . Under Amazon’s schedule, the per-unit fulfillment fee, which covers picking, packing, shipping, customer service, and returns, depends on a product’s size tier and shipping weight (?). The size tier (small standard, large standard, or one of several oversize tiers) is determined by the packaged product’s dimensions and weight. Within a tier, the fee rises in steps with shipping weight. For large standard-size and most oversize products, shipping weight is the greater of the unit weight and the dimensional weight (length $\times$ width $\times$ height in inches, divided by 139); small standard-size products use unit weight. Apparel and dangerous goods have separate rates, and Amazon adds a temporary surcharge during the holiday peak season. Low-priced products also qualify for reduced rates: through the Small and Light program (products priced at \$12 or less in 2023) until August 29, 2023, and through low-price FBA rates (products priced under \$10) thereafter. Amazon revises the schedule periodically; for example, on January 17, 2023, it raised fulfillment fees by \$0.22 per unit on average. In the data, I compute each product’s fee from the schedule in effect and its package dimensions and weight.

revenue Amazon collects from third-party sellers, which depends on how these sellers respond in prices and fulfillment methods. The third line is the total cost Amazon incurs operating its fulfillment service, for both its own and third-party products. To capture potential economies of scale in logistics, I assume $C_{mt}(Q) = A_m Q^b e^{gt}$, where $b < 1$ implies economies of scale and e^{gt} captures a common time trend in fulfillment costs. The last line is an empirical proxy for the two-sided nature of an online marketplace, where θ^c and θ^s are weights capturing how much Amazon internalizes consumer and seller welfare, respectively. This captures the idea that the platform must share some of its revenue with sellers and consumers to keep them on the platform, since the platform's value to consumers increases with the number of sellers it hosts, and vice versa. For tractability, I capture these incentives with weights rather than modeling them explicitly, following common practice in the literature (e.g., Gutierrez, 2021; Yu, 2024).

The fees affect Amazon's objective both directly through revenue and indirectly through sellers' responses in fulfillment methods and prices. On the extensive margin, fees determine which sellers opt into FBA versus FBM, as determined by the equilibrium of seller competition in prices and Prime status. On the intensive margin, fees are passed through into prices. For example, if Amazon raises the FBA fee, sellers with sufficiently low FBM costs will switch out of FBA, while Amazon earns higher fees from the sellers who remain; the fee increase therefore raises revenue per FBA transaction but shrinks the base of transactions to which that higher fee applies. This trade-off is compounded by pass-through: because τ and f^{FBA} enter sellers' marginal cost, a higher fee also induces sellers to raise prices, which lowers demand D_{jmt} and further erodes the fee base Amazon is trying to tax. The extent of pass-through therefore determines how much of the added fee revenue Amazon captures rather than loses through lower volume. Higher third-party fees also shift demand toward Amazon's own products and lower consumer and seller surplus, which Amazon weighs through θ^c and θ^s . Finally, because fulfillment exhibits economies of scale, Amazon has a countervailing incentive to keep FBA volume high: each additional unit routed through FBA lowers the average cost of fulfillment for all units, so Amazon must balance the gain from higher fees against the cost savings from greater FBA volume.

4 Data

4.1 Product Prices and Other Information

The primary data source is Keepa, an online service used by Amazon buyers and sellers to track price histories. Keepa offers an API that allows subscribers to download its data, providing a rich high-frequency panel of product- and offer-level information. For each product, Keepa records descriptive information including the Amazon product code (ASIN), product title, characteristics such as brand, size, category, and package dimensions and weight, and the history of its sales rank, rating, and number of reviews. At the offer level, it records the seller ID, listed price, estimated stock level, fulfillment method, and Prime status. Keepa also records whether a product is listed on eBay, providing a preliminary measure of cross-platform listing and potential competition.⁵

As in Section 3, I define a market as an Amazon product subcategory, using the narrowest definition available to keep products comparable, and a period as a month. The sample covers two subcategories on Amazon.com, facial sunscreen and laptops, over 39 months from December 2020 to February 2024. The facial sunscreen sample contains 833 unique products across 457 brands, with an average of 250 product-offer observations per month. The laptop sample contains 1,693 unique products across 42 brands sold by 1,271 sellers, with an average of 519 product-offer observations per month. Table 1 reports summary statistics for both categories.

Figure 3 shows how sales are distributed across brands and sellers in each category. In an average month, about 140 sunscreen brands and 20 laptop brands are listed, offered by about 180 and 220 sellers, respectively. Both categories are concentrated at the brand level: the four largest brands account for 79% of estimated sunscreen units, with EltaMD alone at 50%, and 80% of laptop units, led by HP and Apple. The monthly brand-level HHI averages 3,390 for sunscreen and 1,916 for laptops. The two categories differ more across sellers. In sunscreen, Amazon itself is the seller for 63% of estimated units, while the 2,125 smallest sellers, each with less than 0.01% of units, together account for under 3%. In laptops, Amazon's share is 17%, and most sales go to mid-sized third-party sellers: the 632 sellers with between 0.01% and 10% of units together account for 80%. The monthly seller-level HHI averages 5,261 for sunscreen and 703 for laptops.

For each third-party seller in the sample, I supplement the product-level data with seller-level information from Keepa's Seller Object API. Most importantly for the cost es-

⁵This measure cannot be used to examine the FTC's argument that the tie makes it more expensive for sellers to multihome, because it is not possible to verify whether the seller on eBay is the same as the seller on Amazon.

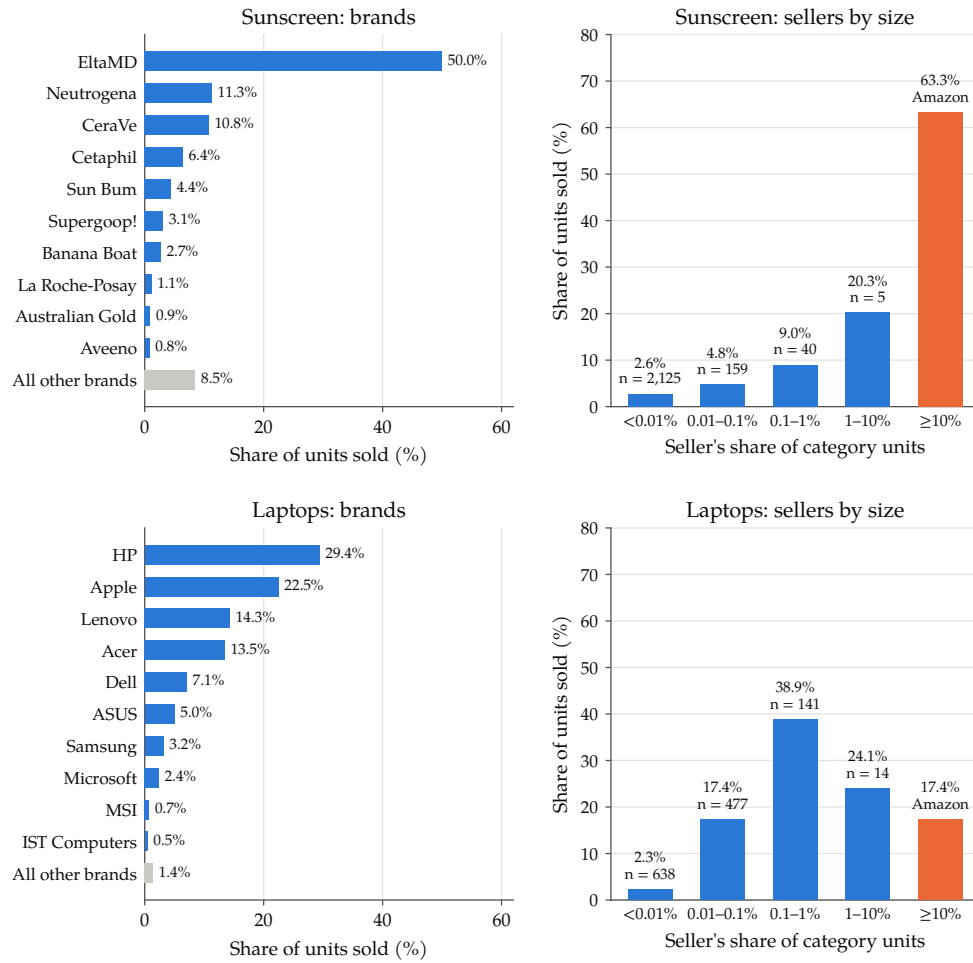


Figure 3: Distribution of Sales across Brands and Sellers

Notes: Left panels: shares of estimated units sold by the ten largest brands. Right panels: share of units held by sellers in each size class, where a seller's size is its share of category units; n is the number of sellers in each class, and Amazon, the only seller with 10% or more of units in either category, is shown in orange. Shares are pooled over December 2020 to February 2024, and units are estimated from sales ranks (Appendix A.1).

Table 1: Summary Statistics

	Facial Sunscreen				Laptops			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
<i>Product characteristics</i>								
Price (\$)	28.73	19.93	0.99	145.00	634.56	446.96	100.20	2598.65
FBA fee (\$)	3.78	0.88	2.16	10.19	7.34	0.88	3.48	12.47
Rating	11.48	17.60	0.00	50.00	17.43	19.94	0.00	50.00
Review count	794.2	3177.3	0	79639	463.8	2475.8	0	39869
eBay price (\$)	24.12	19.44	2.49	231.48	527.40	534.60	79.99	10000.00
<i>Indicator variables</i>		Share (%)			Share (%)			
FBA			48.6				31.0	
Prime			48.7				33.4	
Amazon as seller			13.7				5.7	
eBay cross-listed			11.3				14.2	
Ships from China			0.7				0.8	
<i>Price by fulfillment method</i>		Mean	Std. Dev.		Mean	Std. Dev.		
FBA listings		25.44	16.08			578.14	453.20	
FBM listings		31.85	22.54			659.90	441.81	

Notes: Rating is coded on a 0–50 scale (5-star rating $\times$ 10); products with a missing rating are coded as 0. eBay price is reported conditional on being cross-listed *and* having a nonzero recorded price (sunscreens: $n = 413$ of 1,261 cross-listed observations; laptops: $n = 1,002$ of 2,879).

timation in Section 5, Keepa reports each seller’s business address where the seller has disclosed one, including city, postal code, and country.⁶ I geocode these addresses to obtain each seller’s latitude and longitude, which I then use to construct distances from each seller to Amazon’s nearest fulfillment center, sortation center, and other logistics facilities. Because a seller’s location is a primary determinant of its shipping cost and speed under FBM, it is a key predictor in the model I use to impute FBA sellers’ counterfactual FBM costs (Section 5).

Keepa also provides other seller-level information, including the seller’s name, whether it has any FBA listings, its rating history, and the number of products it lists.

Measure of Sales Quantity

A main data challenge in studying online platforms like Amazon is that sales quantities are not directly observed. Amazon does, however, display a coarse count of recent purchases on many product pages (e.g., “20K+ bought in past month”), which Keepa records over time. These counts have three limitations. First, they are reported in coarse bins, and each displayed count is the lower bound of its bin. Second, they appear only for products

⁶Address disclosure is voluntary and not universal. Sellers who do not provide a business address are dropped from the FBM cost regression sample, as location is essential to that estimation.

with at least 50 purchases in the past month. Third, they are available only at the end of the sample period: for laptops, from October 2023 to February 2024, covering about 5% of observations. To construct a quantity measure for the full sample, I combine these counts with each product’s best-seller rank, which Keepa records throughout the sample.

Using the relationship between sales rank and sales to measure quantities was pioneered by early studies of book sales on Amazon (Chevalier and Goolsbee, 2003; Chevalier and Mayzlin, 2006; Brynjolfsson et al., 2006, 2010). More recently, He and Hollenbeck (2020) estimates this relationship at the product root category level. Following this literature, I assume that sales follow a Pareto distribution, in which a small number of products account for a large share of sales and the rest trail off gradually. Under this assumption, log quantity is a linear function of log sales rank. I estimate this relationship on the subsample with observed purchase counts and use it to construct quantities for all observations. Appendix A.1 reports the estimates. Because the displayed counts are lower bounds, the resulting quantities likely understate sales levels.

4.2 Amazon Fees and Logistics Costs

Both the referral fee and FBA fee schedules are publicly posted on Amazon’s website, and their historical levels can be recovered using the Internet Archive’s Wayback Machine. The referral fee is an ad valorem charge that varies across product categories. Most categories have a referral rate of 15%, while consumer electronics and personal computers carry a rate of 8% and clothing and accessories a rate of 17%. Facial sunscreen falls under Beauty, Health and Personal Care, which charges 15% on items priced above \$10 and 8% on items priced at \$10 or less; laptops are charged 8%. In both categories, the referral rates remain constant throughout the sample period. The FBA fee schedule, by contrast, changes over time: Amazon revises it periodically, for example in January 2023 and February 2024. This contrast suggests that Amazon adjusts its fees mainly through the FBA fee schedule, a point I return to in Section 6.

The FBA fee is a per-unit charge that varies along two dimensions. First, it distinguishes between broad product types, with separate rates for regular (non-apparel) items, apparel, and low-price items (through the Small and Light program until August 2023 and through low-price FBA rates for items priced under \$10 thereafter). Second, within each product type, the fee increases with package size and weight, structured across discrete tiers ranging from small standard to special oversize. In addition, FBA users pay a monthly storage fee per cubic foot of inventory held in Amazon’s warehouses, which is higher for oversize items and during the fourth quarter. Table 2 summarizes package

dimensions and the resulting FBA fees in both categories. Facial sunscreen products are light and compact: the average package weighs 0.48 lb and measures roughly 6.0 by 2.9 by 1.7 inches, placing most products in the lowest size and weight tiers. Their FBA fees range from \$2.16 to \$10.19 per unit, with a mean of \$3.78. Laptops are larger and heavier: the average package weighs 5.4 lb and measures roughly 18.0 by 12.4 by 3.2 inches, and FBA fees range from \$3.48 to \$12.47, with a mean of \$7.34.

Table 2: Package Dimensions and FBA Fees

	Facial Sunscreen				Laptops			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Package weight (lb)	0.48	0.79	0.01	10.87	5.38	1.50	0.04	18.00
Package height (in)	1.67	0.88	0.04	10.47	3.23	0.97	0.75	12.40
Package length (in)	6.02	1.74	0.12	21.10	18.01	2.34	2.01	30.00
Package width (in)	2.92	1.78	0.08	20.98	12.37	1.74	2.01	20.00
Calculated FBA fee (\$)	3.78	0.88	2.16	10.19	7.34	0.88	3.48	12.47

Notes: Statistics for each package dimension exclude observations recorded as exactly zero for that variable (likely missing-data codes). Facial sunscreen: $N = 10,286$ for weight, 10,224 for height, length, and width, and 11,198 for the FBA fee. Laptops: $N = 20,231$ for all variables, none of which has zero values.

To bound sellers' FBM fulfillment costs, I collect USPS retail shipping rates and match them to products based on package dimensions and weight. USPS is a common carrier for small parcels, and Amazon's Buy Shipping program offers FBM sellers discounted labels from USPS and other carriers directly through the platform. The relevant service is USPS Ground Advantage, which prices shipments by weight and delivery zone, where zones proxy for the distance between origin and destination. Retail rates for Ground Advantage start at \$7.30 for packages up to 4 oz shipped within the nearest zones and increase steeply with both weight and distance: a 2 lb package shipped to zone 8 costs \$17.65, compared with \$10.00 for the same package shipped locally.⁷ Since facial sunscreen products typically weigh under 1 lb including packaging, most FBM shipments in this category fall in the lowest weight tiers, with retail rates roughly between \$7.30 and \$11.95 depending on destination zone. These rates are well above the mean FBA fee of \$3.78, suggesting a meaningful cost advantage to FBA for lightweight products, even though sellers who use Buy Shipping pay less than retail rates and FBA sellers also pay storage fees. [For laptops, I apply the Zone 3 rate for each product's package weight.] Because sellers rarely pay full retail rates, I use these rates as an upper bound on FBM costs in the cost estimation (Section 5).

⁷Rates are as of January 2026. USPS introduced Ground Advantage in July 2023, replacing First-Class Package Service, Parcel Select Ground, and Retail Ground (U.S. Postal Service, 2023).

4.3 Delivery Time

I scrape delivery time data directly from Amazon for each product listing, collecting the estimated delivery dates shown to Prime members and to non-members at the time of scraping. The Prime badge on a listing is visible to all consumers, but the delivery time a buyer sees depends on both the listing’s fulfillment method and the buyer’s membership. For FBA listings, Prime members receive faster delivery under Amazon’s fulfillment network, while non-members receive slower standard shipping. For FBM listings other than SFP, Prime members and non-members face the same delivery time, since all orders are shipped through the seller’s own logistics regardless of membership. Delivery dates for Prime members are typically given as a single date, while those for non-members more commonly appear as a range of days, reflecting greater uncertainty in delivery timing; [for ranges, I use the earliest date]. I measure $FastestDelivery_{jmt}$ in equation (1) as the delivery time shown to Prime members, which is the fastest available for the listing.

A delivery time is available for 487 of the 833 facial sunscreen products (58%) and 547 of the 1,693 laptops (32%); the remaining products were likely out of stock or no longer listed at the time of scraping. Delivery times differ sharply with Prime status. Listings with the Prime badge almost always show 2-day delivery, consistent with Amazon’s two-day Prime promise, while listings without the badge average 7.6 days for sunscreen and 4.0 days for laptops. Because the delivery times are measured after the sample period, I apply them to historical observations according to each observation’s Prime status, so a product’s delivery time changes when it moves between Prime and non-Prime. This assumes that a product’s delivery speed under a given fulfillment method is stable over time.

5 Estimation

5.1 Estimation Methods

I estimate the demand, sellers’ problem, and the platform’s problem separately.

5.1.1 Demand

I estimate the demand model using the mixed logit framework of Pakes et al. (1995), implemented via `pyBLP` (Conlon and Gortmaker, 2020). The parameter vector $\theta = (\beta, \beta_{Prime}, \beta_{shipping}, \mu_\alpha, \sigma_\alpha)$ collects all demand parameters. I treat both price p_{jmt} and Prime status $Prime_{jmt}$ as endogenous. Price is endogenous for the standard reason: sellers observe the unobserved

product quality ξ_{jmt} when setting prices, so equilibrium prices are correlated with the demand-side structural error, and estimates that ignore this are typically biased toward zero. Prime status is endogenous for a related but distinct reason: whether a listing carries the Prime badge is determined by the seller’s fulfillment choice, and sellers choose FBA—and hence Prime eligibility—based in part on the same unobserved product characteristics that shift demand, so Prime_{jmt} is also correlated with ξ_{jmt} .

I estimate θ by two-step GMM:

$$\hat{\theta} = \arg \min_{\theta} g(\theta)' \Omega g(\theta), \quad g(\theta) = \frac{1}{N} Z' \xi(\theta),$$

where Z is the matrix of instruments, $\xi(\theta)$ stacks the structural errors recovered via the BLP contraction mapping at each evaluation of the objective, and N is the number of observations. The first step uses $\Omega = (Z'Z/N)^{-1}$; the second uses $\Omega = \hat{S}^{-1}$, where $\hat{S} = \frac{1}{N} \sum_{j,m,t} \hat{\xi}_{jmt}^2 z_{jmt} z'_{jmt}$ is computed from the first-step residuals with centered moments. Standard errors use the corresponding heteroskedasticity-robust sandwich estimator.

The instrument matrix Z includes two sets of instruments. The first set consists of BLP-style instruments, which primarily shift prices: the product’s own exogenous characteristics (rating, number of reviews, whether it ships from China, and its eBay price) and functions of the characteristics of rival products in the same market (including their ratings, package dimensions and weights, and eBay listing status and prices), together with the number of same-brand products in the market. The identifying assumption is that these characteristics shift a product’s differentiation from its rivals, and hence its equilibrium price, while being uncorrelated with ξ_{jmt} .

The second set, following Gutierrez (2021), consists of cost shifters for the fulfillment decision, which primarily shift Prime status: seller fixed effects and Amazon’s fee levels. To generate variation across listings, I construct the FBA fee each product would pay under Amazon’s fee schedule given its package dimensions and weight, whether or not the product uses FBA (for example, \$6.92 plus \$0.16 per half-pound above the first 3 lb in one size tier). This provides product-level variation in the cost of FBA enrollment, and hence in the cost of obtaining Prime eligibility. The identifying assumption is that this fee variation, driven by physical package characteristics that determine Amazon’s fulfillment cost, is uncorrelated with demand shocks and shifts sellers’ fulfillment choices without directly affecting consumer demand. Seller fixed effects capture persistent differences in sellers’ fulfillment costs; using them as instruments requires that seller identity affects demand only through prices and Prime status.

5.1.2 Seller Costs

Given the demand parameters estimated in Section 5.2.1, I recover sellers' total marginal costs by inverting their pricing first-order conditions. Since each observation is either FBA or FBM, I observe only one of the two first-order conditions for a given product in a given month. Dropping the market and period subscripts, for FBA observations,

$$\frac{\partial \pi_j^{FBA}}{\partial p_j} = 0 \implies D_j + \frac{\partial D_j}{\partial p_j} \left(p_j - \frac{c_j + f_j^{FBA}}{1 - \tau} \right) = 0,$$

and for FBM observations,

$$\frac{\partial \pi_j^{FBM}}{\partial p_j} = 0 \implies D_j + \frac{\partial D_j}{\partial p_j} \left(p_j - \frac{c_j + f_j^{FBM}}{1 - \tau} \right) = 0,$$

where demand D_j and its derivative are evaluated at the product's observed Prime status. Inverting the condition that corresponds to each observation's fulfillment method recovers its total marginal cost, the sum of production and fulfillment costs:

$$c_j + f_j = (1 - \tau) \left(p_j + \frac{D_j}{\partial D_j / \partial p_j} \right), \quad (6)$$

where $f_j = f_j^{FBA}$ for FBA observations and $f_j = f_j^{FBM}$ for FBM observations. Because $D_j / (\partial D_j / \partial p_j) = s_j / (\partial s_j / \partial p_j)$, the recovered costs do not depend on market size.

To separate production costs from fulfillment costs, I proceed in two steps. First, for FBA observations, I compute f_j^{FBA} directly from Amazon's fee schedule, so production cost c_j follows immediately from equation (6). Second, for FBM observations, f_j^{FBM} is unobserved, so I cannot separate the two components directly. Instead, I regress the recovered c_j for FBA observations on a rich set of product characteristics, extracted from product titles and descriptions using a large language model, together with brand and time fixed effects. For facial sunscreen, these include SPF level and indices for features such as mineral or sensitive-skin formulations; for laptops, RAM, storage, screen size, and processor tier, along with their squares and pairwise interactions. I use the fitted model to predict production costs for FBM observations and recover their FBM costs as total marginal cost minus predicted production cost. This approach assumes that, conditional on these characteristics, production costs do not differ systematically between FBA and FBM products.

To study sellers' strategic behavior in counterfactual scenarios, I also need the FBM costs that sellers who choose FBA would face if they fulfilled orders themselves. I regress

the recovered FBM costs on package size and weight, seller location, interactions between size or weight and location, and time fixed effects:

$$f_{jmt}^{FBM} = W_{jmt}' \psi + \eta_t + v_{jmt}, \quad jmt \in \text{FBM}, \quad (7)$$

where W_{jmt} collects the package and seller characteristics. I apply the fitted coefficients $\hat{\psi}$ and $\hat{\eta}_t$ to FBA observations' package and seller characteristics to predict the FBM cost each FBA seller would face. To keep these predictions economically sensible, I cap them at the corresponding USPS retail shipping rate r_{jmt}^{USPS} , since a seller could always ship through USPS at retail rates:

$$\hat{f}_{jmt}^{FBM} = \min \left\{ W_{jmt}' \hat{\psi} + \hat{\eta}_t, r_{jmt}^{USPS} \right\}, \quad jmt \in \text{FBA}. \quad (8)$$

Conversely, for FBM observations, the cost of switching to FBA is the FBA fee f_{jmt}^{FBA} computed from Amazon's fee schedule.

5.1.3 Platform

I impose two restrictions on the platform's fee-setting problem in equation (5) to make estimation tractable. First, Amazon's actual FBA fee schedule is a high-dimensional step function of a product's size tier and shipping weight, with the fee rising in discrete increments as weight increases within a tier. Rather than modeling the choice of this entire schedule, I restrict it to a market-period-specific multiplier on a product-specific base fee:

$$f_{jmt}^{FBA} = \lambda_{mt} \bar{f}_{jt}^{FBA}, \quad (9)$$

where the base fee $\bar{f}_{jt}^{FBA}$ is computed from the historical FBA fee schedule in effect in period t and product j 's package dimensions and weight. The parameterization is normalized so that $\lambda_{mt} = 1$ reproduces the observed fees, so a counterfactual λ_{mt} scales the entire schedule up or down uniformly rather than changing its shape across products. Amazon's choice of the FBA fee schedule thus reduces to the choice of λ_{mt} .

Because any feasible subset would cover only a small fraction of the catalog, adding a handful of categories would do little to make the sample representative. I instead choose two categories that differ sharply along the dimensions that drive the platform's trade-offs, so that together they approximate the heterogeneity across Amazon's catalog. Facial sunscreen is a light, low-priced category with a 15% referral rate, in which the FBA fee is about 13% of the average price and roughly half of listings use FBA. Laptops are heavy and expensive, with an 8% referral rate, an FBA fee of about 1% of the average price, and

FBA use by about a third of listings. The returns to scale b and the welfare weights θ^s and θ^c are properties of the platform rather than of any one category, so they must rationalize the observed fees in both categories at once. Choosing categories that differ this much makes that requirement informative: the shared parameters cannot be fitted to a single, idiosyncratic type of product.

I specify each category's fulfillment cost as

$$C_{mt}(Q_{mt}) = A_m Q_{mt}^b e^{gt}, \quad (10)$$

where $Q_{mt} = \sum_{j \in \mathcal{J}_m} FBA_{jmt} D_{jmt}$ is category m 's FBA order volume, constructed from estimated market shares and category-specific market sizes. The scale A_m differs across categories, while the returns to scale b and the cost growth rate g are shared. The term e^{gt} captures the common upward trend in fulfillment costs over the sample. I calibrate g directly from the fee data, as the within-product growth rate of FBA fees in a regression with product fixed effects: $\hat{g} = 0.00815$ per month (about 10.3% per year), with nearly identical estimates for sunscreen (0.84% per month) and laptops (0.80% per month). Without this trend, b would absorb the steady growth in fees over the sample, and estimating g jointly with the other parameters leaves the objective nearly flat. Because A_m is category-specific, b is identified from how each category's FBA volume, and hence its marginal fulfillment cost, varies over time, rather than from differences in volume levels across categories. The estimates should therefore be read as describing the cost relationship over the range of volumes these two categories generate, not as a literal estimate of Amazon's network-wide cost function.

Pooling the two categories also helps identify the platform's preferences from its choice of referral rates. In the data, the referral rate is constant over time within a category but differs across categories ($\tau_{\text{sunscreen}} = 0.15$, $\tau_{\text{laptop}} = 0.08$). Because τ_m never moves within a category, its first-order condition provides only a single moment per category, averaged across periods. Estimating the two categories jointly requires both categories' τ_m conditions to hold at the same (b, θ^s, θ^c) , which disciplines these parameters far more than either category's condition could alone.

Given this setup, I estimate the parameters $(A_{\text{sunscreen}}, A_{\text{laptop}}, b, \theta^s, \theta^c)$ using the platform's first-order conditions as moment restrictions. I maintain that the observed fees $(\tau_m, \lambda_{mt} = 1)$ are optimal given the platform's objective in equation (5): Amazon has already solved its fee-setting problem, and the parameters I recover are those consistent with the observed fees being a local optimum. This revealed-preference approach is standard for estimating conduct parameters and avoids calibrating the cost function and the

weights (θ^s, θ^c) ex ante. Let Π_{mt} denote Amazon's profit in category m and period t —its first-party selling profit plus third-party fee revenue, net of fulfillment cost—and let SS_{mt} and CS_{mt} denote third-party seller surplus and consumer surplus. Because τ_m is constant within a category while λ_{mt} is set in every category-period, the two families of first-order conditions differ in how they aggregate over time:

$$\sum_{t=1}^{T_m} \left[\frac{\partial \Pi_{mt}}{\partial \tau_m} + \theta^s \frac{\partial SS_{mt}}{\partial \tau_m} + \theta^c \frac{\partial CS_{mt}}{\partial \tau_m} \right] = 0, \quad \forall m, \quad (11)$$

$$\frac{\partial \Pi_{mt}}{\partial \lambda_{mt}} + \theta^s \frac{\partial SS_{mt}}{\partial \lambda_{mt}} + \theta^c \frac{\partial CS_{mt}}{\partial \lambda_{mt}} = 0, \quad \forall m, t. \quad (12)$$

With two categories and $T = 39$ common periods, equation (11) contributes two moments and equation (12) contributes $2 \times 39 = 78$, for 80 moment conditions in total. I estimate the five parameters by minimizing the sum of squared residuals across all 80 stacked moments.

The derivatives in equations (11) and (12) are not available in closed form, since Π_{mt} , SS_{mt} , and CS_{mt} are outputs of the seller equilibrium. I compute them by central finite differences, re-solving the seller equilibrium in each category and period at the observed fees and at small perturbations of τ_m and λ_{mt} in each direction. These equilibrium solves return fee revenue, surplus, and FBA volume but not the fulfillment cost, whose parameters are being estimated, so I add the cost term analytically. Because each category's fulfillment cost depends only on its own FBA volume, the derivative of the cost term with respect to a fee instrument $\text{fee}_m \in \{\tau_m, \lambda_{mt}\}$ is

$$\frac{\partial C_{mt}}{\partial \text{fee}_m} = A_m b \underbrace{Q_{mt}^{b-1} e^{gt}}_{Z_{mt}(b)} \frac{\partial Q_{mt}}{\partial \text{fee}_m}. \quad (13)$$

Conditional on b , each stacked first-order condition is therefore linear in $A_{\text{sunscreen}}, A_{\text{laptop}}, \theta^s$, and θ^c :

$$\phi_{mt} - A_m Z_{mt}(b) + \theta^s \omega_{mt}^s + \theta^c \omega_{mt}^c = 0, \quad (14)$$

where ϕ_{mt} is the derivative of Amazon's profit excluding fulfillment cost, and ω_{mt}^s and ω_{mt}^c are the derivatives of seller and consumer surplus. For a given b , the remaining four parameters solve an 80×4 linear least-squares problem in closed form, and I recover b by a one-dimensional search over the resulting objective. I compute standard errors by a paired bootstrap that resamples periods with replacement, using the same resampled periods for both categories in each draw so that the shared parameters are estimated from

Table 3: Demand Estimation

Variable	Facial sunscreen	Laptop
<i>Nonlinear coefficients</i>		
σ_{price}	1.40 (0.36)	0.16 (1.25)
μ_{price}	2.40 (0.78)	4.76 (1.55)
<i>Linear coefficients</i>		
Prime	0.057 (0.340)	0.187 (1.05)
Fastest delivery (#days)	-0.095 (0.060)	-0.0098 (0.407)
Product fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Observations	1,915	4,566

Notes: This table reports estimated demand parameters for the two selected product categories. α captures price sensitivity, where the facial sunscreen prices are normalized by 10 and the laptop prices are normalized by 200.

a common calendar history.

5.2 Estimates

5.2.1 Demand Parameters

I estimate the demand model in equation (1) separately for the two product categories, facial sunscreen (referral fee 15%) and laptops (referral fee 8%). Table 3 reports the estimates. The average own-price elasticity is 2.14 in magnitude for sunscreen and 3.10 for laptops, within the range of existing estimates (e.g., Gutierrez, 2021). The average willingness to pay for the Prime badge, holding delivery speed fixed, is \$0.86 for sunscreen and \$35 for laptops, or about 3% and 5.5% of the average price. The average willingness to pay for one day faster delivery is \$1.43 for sunscreen and \$1.89 for laptops, or about 5% and 0.3% of the average price. Relative to price, consumers value faster delivery more in sunscreen but the badge itself more in laptops. One interpretation is that the badge matters most for expensive purchases, where reliable fulfillment and easy returns are worth more.

5.2.2 Production Cost Regression

As described in Section 5.1.2, I recover production costs directly for FBA observations and predict them for FBM observations from a regression on product characteristics. For each category, I regress the recovered production costs of FBA observations on product characteristics extracted from Amazon product descriptions, together with brand and time fixed effects:

$$c_{jmt} = H_j' \rho + \kappa_{b(j)} + \zeta_t + \varepsilon_{jmt}, \quad jmt \in \text{FBA}, \quad (15)$$

where H_j collects the characteristics and their transformations, $\kappa_{b(j)}$ is a fixed effect for product j 's brand, and ζ_t is a month fixed effect. Because the regression is used to predict costs, I do not give individual coefficients a causal interpretation.

For facial sunscreen, H_j includes the listing's SPF level and a set of ingredient- and formulation-related indices, together with their squares and pairwise interactions, for 44 characteristic terms; with the fixed effects, the model has 123 regressors. I estimate it by OLS. Table ?? reports the coefficients with the largest magnitudes. SPF category has the largest coefficients: high-SPF products cost about \$1.65 less to produce than the omitted low-SPF category, and medium-SPF products about \$0.25 less. The active, moisture, sensitive, and cosmetic indices all carry positive coefficients, so products marketed with more of these attributes tend to cost more to produce. The squared and interaction terms are an order of magnitude smaller, suggesting that the relationship between these indices and cost is close to linear over the relevant range. The model fits well, with an R^2 of 0.715.

For laptops, H_j includes 66 characteristics, such as processor brand, display type, ports, operating system, weight, storage type, and indices of performance and portability, along with indicators for missing specifications. The regression also includes the 116 demand instruments from Section 5.2.1, for 260 regressors in total. Because many of these regressors are correlated, I estimate the model by ridge regression, with the penalty parameter selected by five-fold cross-validation. Table 4 reports the coefficients with the largest magnitudes. Premium components carry the largest positive coefficients: Qualcomm and Apple processors add about \$215 and \$200 to production cost, an OLED display about \$86, and Thunderbolt and USB-C ports about \$50 and \$44. Several missing-specification indicators also carry large coefficients, suggesting that listings that omit specifications differ systematically from those that report them. The model fits less well than for sunscreen: the in-sample R^2 is 0.515 and the cross-validated R^2 is 0.265.

I then use the fitted models to predict production costs $\hat{c}_{jmt}$ for FBM observations from the same characteristics. Because laptop production costs are large relative to fulfillment costs, prediction errors in $\hat{c}_{jmt}$ translate into large errors in the implied FBM fulfillment

costs, which are therefore largely determined by the bounds described in Section 5.1.2.

Table 4: FBA Production Cost Regressions

<i>Panel A: Facial Sunscreen</i>		<i>Panel B: Laptops</i>	
	Coefficient		Coefficient
Intercept	2.95	CPU brand: Qualcomm	214.53
SPF category: high	−1.65	CPU brand: Apple	199.56
SPF category: medium	−0.25	OLED display	85.59
Active index	0.17	OS: unknown	74.56
Moisture index	0.10	OS: Windows 10	56.31
Sensitive index	0.07	Thunderbolt port	49.95
Cosmetic index	0.03	USB-C port	43.54
Premium × Sensitive index	0.013	Performance index	43.03
Premium index squared	−0.012	OS: macOS	40.91
Sensitive index squared	−0.010	Weight (lb)	39.73
Time fixed effects	Yes	Time fixed effects	Yes
Brand fixed effects	Yes	Brand fixed effects	Yes
Observations	5,237	Observations	6,269
R^2	0.715	R^2	0.515

Notes: Estimates of equation (15) on FBA observations. Each panel reports the characteristic coefficients with the largest magnitudes; Panel B omits indicators for missing specifications. For facial sunscreen, these come from 44 characteristic terms (base variables, squared terms, interactions, and binned categories); with the fixed effects, the model has 123 regressors. For laptops, the model has 260 regressors (66 characteristics, 116 demand instruments, 38 time fixed effects, and 40 brand fixed effects).

5.2.3 Fulfillment Cost: Recovering FBM Costs

With predicted production costs in hand, I recover each FBM observation’s fulfillment cost as the residual of its total marginal cost, $f_{jmt}^{FBM} = (1 - \tau_m) p_{jmt} (1 - 1/\eta_{jmt}) - \hat{c}_{jmt}$, where η_{jmt} is the absolute value of the product’s own-price elasticity, and estimate equation (7) on these recovered costs. Table 5 shows that package weight is the strongest and most statistically significant predictor of FBM fulfillment cost, consistent with shipping carriers pricing primarily on weight. Package length-squared is also significant, suggesting a convex relationship between length and cost that may reflect dimensional-weight pricing rules used by carriers for oversized packages. The higher-order polynomial and interaction terms among package characteristics are mostly insignificant, indicating that, once linear weight and the length-squared term are accounted for, additional nonlinear structure in the package-dimension variables adds little explanatory power. Both latitude and longitude of the seller’s address are statistically significant, while the more granular distance-to-facility variables (nearest fulfillment center, sorting center, or other facility) are not. This suggests that fulfillment cost varies systematically with a seller’s broad geographic location — plausibly capturing regional shipping-zone pricing — more than

with fine-grained proximity to specific Amazon facilities. The model explains a moderate share of the variation in recovered FBM costs ($R^2 = 0.645$), which I view as reasonable given that f_{jt} is itself an indirectly recovered residual rather than a directly observed cost, so measurement error in MC_{jt} and $\widehat{PC}_{jt}$ propagates into f_{jt} and limits attainable fit.

I then use the fitted model to predict the FBM cost each FBA seller would face if it fulfilled orders itself, capped at the applicable USPS retail rate as in equation (8). The cap prevents implausibly high predictions for products outside the support of the FBM sample.

Table 5: FBM Cost Regression

Variable	Coefficient	Std. error
Constant	4.38**	(1.76)
<i>Package size and weight</i>		
Package weight	35.50***	(10.03)
Package length	1.01	(1.76)
Package height	0.83	(3.34)
Billable weight	-45.53	(50.22)
Girth	-0.42	(1.67)
Volume	0.29	(0.36)
<i>Polynomial and interaction terms</i>		
Weight squared	24.48	(68.03)
Weight cubed	-24.88	(38.64)
Length squared	2.22***	(0.79)
Volume squared	0.009	(0.016)
Weight $\times$ length	0.61	(17.65)
Weight $\times$ girth	0.001	(0.016)
Weight $\times$ volume	-1.35	(4.36)
Length $\times$ girth	0.001	(0.001)
Billable weight $\times$ girth	0.0003	(0.015)
Billable weight $\times$ volume	0.77	(4.98)
<i>Seller location</i>		
Latitude	0.095***	(0.029)
Longitude	0.027***	(0.009)
Distance to nearest fulfillment center (km)	0.0006	(0.0089)
Distance to nearest sortation center (km)	0.0007	(0.0009)
Distance to nearest Amazon facility (km)	-0.0017	(0.0091)
Month fixed effects	Yes	
Observations	4521	
R^2	0.645	

Notes: OLS estimates of equation (7) on FBM observations with a disclosed seller address. The dependent variable is the recovered FBM fulfillment cost. Robust standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$.

5.2.4 Platform Parameters

Table 6 reports the estimates of the platform’s cost and conduct parameters. Standard errors are computed via a paired-period bootstrap: I resample periods with replacement, using the same resampled periods for both categories, re-estimate the platform parameters on each resample with g held at its calibrated value, and report the empirical standard deviation of $(\hat{A}_{\text{sunscreen}}, \hat{A}_{\text{laptop}}, \hat{b}, \hat{\theta}^s, \hat{\theta}^c)$ across resamples. Because the bootstrap holds the demand and seller-cost estimates fixed, these standard errors do not reflect uncertainty from those earlier steps and likely understate the total uncertainty.

The returns-to-scale parameter is $\hat{b} = 0.835$: doubling a category’s FBA volume raises its total fulfillment cost by a factor of $2^{0.835} \approx 1.78$, lowering the average cost per order by about 11%. The 95% confidence interval, however, includes constant returns to scale. The cost-scale parameters A_m depend on the units of Q_{mt} and are not directly interpretable. The estimated weights indicate that Amazon values a dollar of third-party seller surplus about as much as a dollar of its own profit ($\hat{\theta}^s = 0.99$, statistically indistinguishable from one) and a dollar of consumer surplus at about 67 cents ($\hat{\theta}^c = 0.67$). These weights summarize the platform’s two-sided incentives in reduced form rather than describing literal preferences.

Table 6: Platform Parameter Estimates

Parameter	Estimate	Std. error	95% confidence interval
$A_{\text{sunscreen}}$ (fulfillment cost scale)	39.41	(30.48)	[4.16, 121.24]
A_{laptop} (fulfillment cost scale)	193.55	(135.81)	[24.36, 542.91]
b (returns to scale)	0.835	(0.067)	[0.742, 1.027]
θ^s (seller surplus weight)	0.991	(0.010)	[0.975, 1.013]
θ^c (consumer surplus weight)	0.667	(0.081)	[0.547, 0.864]

Notes: GMM estimates from the platform’s first-order conditions in equations (11) and (12), with the cost growth rate fixed at $\hat{g} = 0.00815$ per month. Standard errors and 95% confidence intervals come from a paired bootstrap over periods with 2000 draws.

Figure 4 compares the average FBA fee per unit with the marginal fulfillment cost implied by the platform estimates. In both categories, the FBA fee lies below the estimated marginal cost in every month of the sample. For sunscreen, the fee averages \$3.45, against an estimated marginal cost of \$5.14. For laptops, the gap is much larger: the fee averages \$7.01, about one-fifth of the estimated marginal cost. In both categories, the referral fee Amazon collects on an average sale (about \$4 for sunscreen and \$51 for laptops) exceeds this shortfall. The pattern is consistent with Amazon keeping the per-unit FBA fee low and earning its margin through the ad valorem referral fee.

The estimated returns-to-scale parameter, $\hat{b} = 0.835$, implies that a 10% increase in a

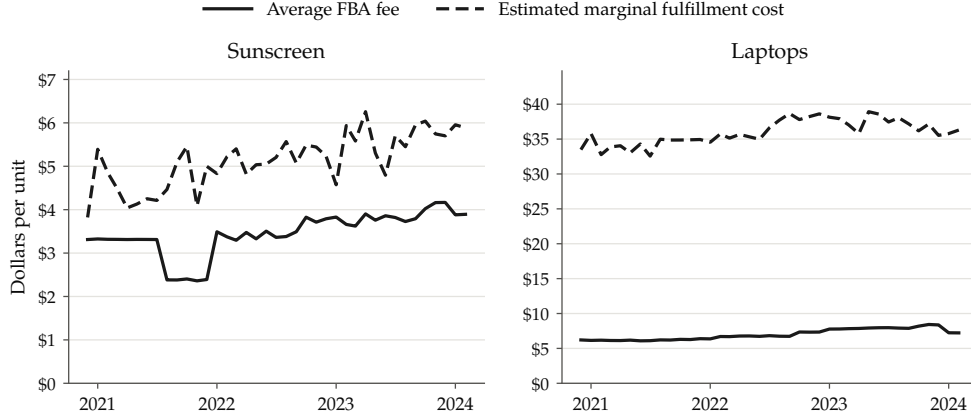


Figure 4: FBA Fees and Estimated Marginal Fulfillment Cost

Notes: The FBA fee is the volume-weighted average fee per FBA unit in each month. The marginal fulfillment cost is $A_{mb} Q_{mt}^{b-1} e^{\hat{g}t}$, evaluated at the estimates in Table ?? and each month's FBA unit volume Q_{mt} .

category's FBA volume raises Amazon's cost of fulfilling that category by about 8.3%. Houde et al. (2023) also find increasing returns in Amazon's fulfillment network, but for one component of fulfillment cost rather than the total cost of operating FBA. They model employment at each Amazon facility as a power function of the orders it processes and estimate an exponent of 0.47, using cross-sectional variation in 2017 employment across facilities and converting employment into labor cost with local retail wages. The two parameters therefore measure different margins. Theirs describes how labor cost at a single facility scales with the orders that facility processes. Mine describes how Amazon's total cost of fulfilling a category's FBA orders, which covers picking, packing, shipping, customer service, and returns, scales with the category's total order volume.

6 Counterfactuals

To measure the overall effect of tying the Prime badge with using FBA, I conduct counterfactual analysis using the estimated model. I consider two scenarios motivated by recent policy discussions: (i) allowing sellers with fast deliveries to qualify for the Prime badge without using FBA, and (ii) complete removal of the Prime badge. For each counterfactual, I solve for the equilibrium for an example time period June 2023.

1. **Seller Fulfilled Prime (SFP).** SFP is an existing Amazon program, but take-up is very low because sellers must meet prequalification conditions, pass a 30-day trial period, and satisfy strict ongoing performance requirements (Section 2). In this

counterfactual, I remove these entry barriers and let any seller whose delivery meets Amazon’s two-day Prime standard qualify for the badge automatically, regardless of fulfillment method. This breaks the link between the badge and FBA while preserving the badge’s association with fast delivery. In June 2023, 5% of FBM facial sunscreen listings and 27% of FBM laptop listings meet this standard.⁸

2. **Removing the Prime Badge.** In the second counterfactual, I remove the Prime badge while allowing consumers to observe shipping times, setting $\mathbf{1}[Prime_{jt}] = 0$ for all products. This eliminates Amazon’s ability to generate demand for FBA by tying it to Prime eligibility.

Both counterfactuals change only the definition of $Prime_{jmt}$, holding β_{Prime} and the rest of the demand system fixed:

$$Prime_{jmt} = \begin{cases} FBA_{jmt} & \text{Baseline} \\ \max\{FBA_{jmt}, \mathbf{1}[FastestDelivery_{jmt} \leq 2]\} & \text{SFP} \\ 0 & \text{No Prime badge} \end{cases}$$

In each counterfactual, sellers re-optimize prices and fulfillment choices in response to the new eligibility rule, and the platform re-optimizes its fees $(\tau_m^*, \lambda_{mt}^*)$ taking these responses into account.

SFP approximates remedies that regulators have pursued. In 2022, the European Commission accepted commitments from Amazon to set non-discriminatory criteria for Prime eligibility and to let Prime sellers choose their own carriers (European Commission, 2022), and the FTC alleges that tying Prime eligibility to FBA coerces sellers into using Amazon’s fulfillment service (Federal Trade Commission, 2023). Under SFP, qualifying sellers can obtain Prime eligibility while fulfilling orders through their own logistics rather than through Amazon’s fulfillment network.

The welfare effects of both counterfactuals depend on how β_{Prime} is interpreted. As discussed in Section 3.1, β_{Prime} may reflect true utility from buying a Prime product, controlling for delivery speed, or choice utility, through which the badge shapes choices without benefiting consumers. Under SFP, newly qualified sellers receive the same demand boost as FBA sellers, and whether this boost benefits consumers depends on which interpretation holds. Removing the badge makes the distinction sharper. If β_{Prime} reflects

⁸This assumes that each seller’s FBM fulfillment option, including both its cost and its delivery speed, is fixed. For example, a seller cannot switch to a faster but more expensive shipping service to qualify for Prime; its only fulfillment choice is between FBA and FBM.

true utility, consumers lose an attribute they value. If it reflects choice utility, removing the badge removes a source of demand that did not benefit consumers, so the lost badge value should not count as a welfare loss, even though demand and prices still change. I therefore report the change in consumer surplus under two polar assumptions: that β_{Prime} is entirely true utility, and that it is entirely choice utility. Because consumer surplus is linear in the share of β_{Prime} that reflects true utility, holding equilibrium choices fixed, any intermediate case lies between these two bounds.

Outcomes

Table 7 reports the equilibrium fees, FBA share, average price, consumer surplus, and third-party seller surplus under the baseline and each counterfactual, separately for facial sunscreen and laptops. The *Baseline (opt.)* row reports the equilibrium when Amazon optimally sets (τ^*, λ^*) given the demand, cost, and platform parameters estimated in Sections 5.2.1–5.2.4. The re-optimized fees are close to the observed levels. The baseline referral fees ($\tau^* = 0.154$ for sunscreen and 0.090 for laptops) are within about one percentage point of the observed rates (0.15 and 0.08). The FBA fee multipliers are within about 30% of the observed level of one, lower for sunscreen ($\lambda^* = 0.69$) and higher for laptops ($\lambda^* = 1.18$). The model also matches the observed sunscreen FBA share closely but overpredicts FBA adoption for laptops.

Relative to the baseline, SFP lowers the FBA share in both categories, from 63.6% to 58.5% for sunscreen and from 88.2% to 74.3% for laptops, as some sellers who used FBA only to obtain the Prime badge switch to FBM once the badge no longer requires it. Removing the badge lowers FBA adoption further, especially for laptops, where the FBA share falls to 7.7%. Part of this collapse reflects Amazon’s fee response, as the optimal laptop FBA fee multiplier rises from 1.18 to 1.42. Even so, the result suggests that in this category the badge, rather than a cost advantage of FBA, sustains most FBA use. Average sunscreen prices rise under both counterfactuals, from \$32.09 in the baseline to \$33.97 under SFP and \$34.30 without the badge, while average laptop prices change by less than 1%.

Table 7: Counterfactual Equilibrium Outcomes

Scenario	Sunscreen						Laptop					
	τ^*	λ^*	FBA%	Avg P	CS	SS	τ^*	λ^*	FBA%	Avg P	CS	SS
Baseline (opt.)	0.1544	0.6900	63.59%	\$32.09	\$2.043M	\$1.357M	0.0900	1.1832	88.17%	\$752.84	\$18.20M	\$5.227M
SFP	0.2952	0.7262	58.54%	\$33.97	\$1.827M	\$1.074M	0.0656	1.1859	74.28%	\$752.88	\$18.44M	\$5.578M
No Prime	0.3240	0.6513	54.90%	\$34.30	\$1.883M	\$1.016M	0.1370	1.4190	7.70%	\$756.59	\$16.02M	\$4.470M

The data level of τ is 0.15 for facial sunscreen and 0.08 for laptop, and the data level of λ is 1.

Figure 5 shows the implied price distributions under each scenario for both categories, illustrating that the counterfactual price increases documented in Table 7 are broad-based rather than concentrated in the tails of the distribution.

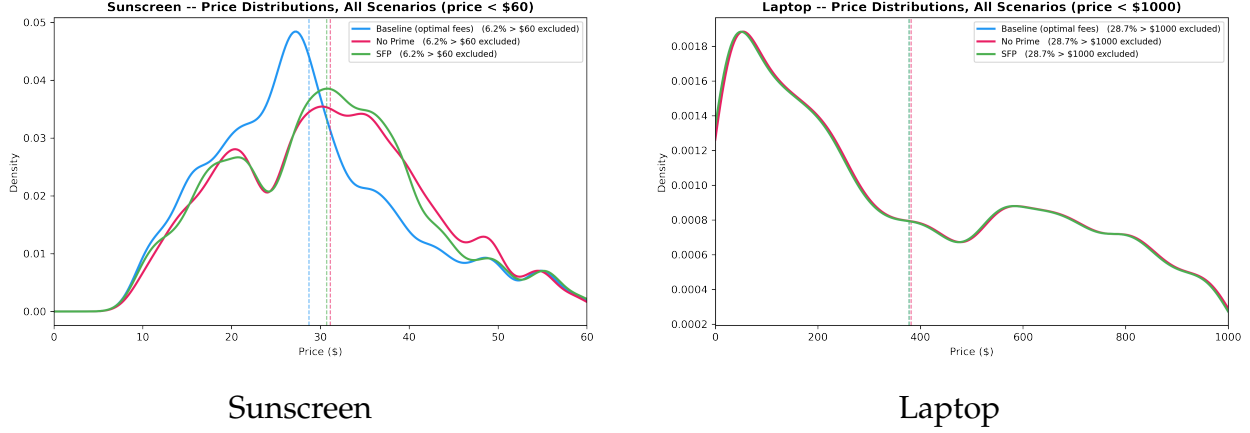


Figure 5: Price Distributions Across Counterfactuals

Consumer Surplus and the True-versus-Choice Utility Bound

As discussed above, the welfare interpretation of any change in Prime eligibility depends on whether β_{Prime} reflects true or choice utility. If β_{Prime} reflects true utility, standard consumer surplus measures welfare. If it reflects choice utility, the badge shifts choices without benefiting consumers, so the conventional log-sum form must be corrected: I subtract only the share-weighted contribution of β_{Prime} from consumer surplus following (Allcott, 2013; Train, 2015; Cao et al., 2024).⁹ This removes the badge’s contribution to measured consumer surplus without altering the choices—prices, fulfillment, and the resulting market shares—that consumers and sellers actually made in that equilibrium. The baseline equilibrium’s standard consumer surplus is therefore the true-utility reference point, and its corrected form is the choice-utility reference point.

Table 8 reports consumer surplus for the sunscreen category, the laptop category, and their sum under the baseline, SFP, and No Prime scenarios, together with the baseline and SFP corrected for choice utility.¹⁰ Table 9 then reports the percentage change in

⁹Train (2015) shows that when choice utility and true utility differ, expected consumer surplus equals the standard log-sum formula applied to choice utility plus the choice-probability-weighted average of the gap between true and choice utility, with choice probabilities held at their actual values (his Eqs. 1–4; he credits Allcott (2013) as an originator of the procedure). In the present setting, the gap for product j is $-\beta_{Prime}Prime_{jmt}$, so the correction subtracts $(\beta_{Prime}/\bar{\alpha})\sum_{j \in \mathcal{J}_{mt}} s_{jmt} Prime_{jmt}$ from expected consumer surplus per consumer, where $\bar{\alpha}$ is the mean price coefficient.

¹⁰No product carries the badge under No Prime, so the correction leaves its consumer surplus unchanged, and the same figure applies under both interpretations.

joint consumer surplus for each counterfactual relative to the reference point for each interpretation—the baseline consumer surplus if β_{Prime} reflects true utility, and the corrected baseline if it reflects choice utility.

Table 8: Consumer Surplus by Scenario

Scenario	Sunscreen CS	Laptop CS	Joint CS
Baseline (opt.) $\leftarrow$ true-utility ref.	\$2.043M	\$18.20M	\$20.24M
Baseline (corrected for choice utility) $\leftarrow$ choice-utility ref.	\$1.913M	\$16.61M	\$18.52M
SFP	\$1.827M	\$18.44M	\$20.26M
SFP (corrected for choice utility) $\leftarrow$ choice-utility	\$1.710M	\$16.61M	\$18.32M
No Prime	\$1.883M	\$16.02M	\$17.90M

Table 9: Change in Joint Consumer Surplus, by Bound

Scenario (Joint CS)	Δ vs. Baseline [$\beta_{prime} = \text{true utility}$]	Δ vs. Corrected Baseline [$\beta_{prime} = \text{choice utility}$]
SFP	+0.1%	−1.1%
No Prime	−11.6%	−3.3%

Two results stand out. First, SFP is close to neutral for joint consumer surplus under either interpretation of β_{Prime} : it rises by 0.1% if β_{Prime} reflects true utility and falls by 1.1% if it reflects choice utility. The joint figure, however, masks opposite effects across categories. Sunscreen consumer surplus falls by 10.6% under either interpretation, as Amazon nearly doubles the sunscreen referral fee and average prices rise by 6% (Table 7). Laptop prices barely change, yet laptop consumer surplus still rises by 1.3% under the true-utility interpretation, reflecting the value of the badges extended to qualifying FBM listings; under the choice-utility interpretation, it is unchanged. Second, and more strikingly, removing the Prime badge reduces joint consumer surplus under *both* interpretations—by 11.6% if β_{Prime} reflects true utility and by 3.3% even if it reflects choice utility. This second result is the more policy-relevant one. Even if none of the estimated preference for Prime reflects a genuine service benefit, and consumers respond to the badge only because of its salience, removing the badge still leaves consumers worse off. Holding prices and fulfillment fixed, removing a badge that only distorts choices would weakly raise consumer surplus.¹¹ The loss therefore comes from the equilibrium response: Amazon raises its referral fees in both categories, prices rise, and FBA use falls, which slows delivery. Laptops again show that the average price is a poor guide to consumer surplus. The

¹¹Under the choice-utility interpretation, a consumer who chooses on true utility does at least as well, measured in true utility, as one whose choice is distorted by the badge.

average laptop price rises by only 0.5%, yet laptop consumer surplus falls by 3.6% even under the choice-utility interpretation. The average price across listings does not capture which listings consumers buy or how quickly their orders arrive.

Effects on Third-Party Sellers

Table 10 decomposes the change in third-party seller surplus under each counterfactual into three channels.¹² *Badge eligibility* isolates the direct effect of SFP’s qualification rule, holding baseline prices, fees, and fulfillment choices fixed; the analogous *badge removal* row for No Prime isolates the direct effect of stripping the badge, again at baseline prices, fees, and fulfillment. *Fee/price response* then adds the platform’s re-optimized fees (τ^*, λ^*) and sellers’ resulting repricing on top of the badge change, while still holding fulfillment mode fixed at its baseline value. Finally, *switching* allows sellers to also re-optimize their fulfillment choice (FBA versus FBM) in response to the new badge rule and fees, yielding the *total* change in seller surplus. Unlike consumer surplus, seller surplus does not depend on whether β_{Prime} reflects true or choice utility, since sellers benefit from the badge’s effect on demand either way.

Table 10: Third-Party Seller Surplus Decomposition

SFP	ΔSS	No Prime	ΔSS
Badge eligibility	+\$18.7K	Badge removal	−\$696.0K
Fee/price response	+\$0.4K	Fee/price response	−\$27.0K
Switching	+\$49.2K	Switching	−\$129.2K
Total	+\$68.4K	Total	−\$852.3K

The two counterfactuals affect sellers through very different channels. Under SFP, seller surplus rises by \$68.4K overall, and most of this gain comes from switching: \$49.2K, or about 72%, comes from sellers re-optimizing their fulfillment choice once Prime no longer requires FBA. This is consistent with the FBA-share decline in Table 7, since a seller switches from FBA to FBM only if doing so raises its profit given its rivals’ choices. The direct value of badge eligibility (\$18.7K) and the fee/price response (\$0.4K) are smaller. The aggregate, however, masks opposite effects across categories. Sunscreen seller surplus falls by 21%, while laptop seller surplus rises by 7% (Table 7), as Amazon nearly doubles the sunscreen referral fee but lowers the laptop referral fee. The small aggregate fee/price response therefore likely nets out a loss for sunscreen sellers against a gain for

¹²The decomposition is sequential, so each channel’s contribution depends on the order in which the channels are added.

laptop sellers. Under No Prime, by contrast, seller surplus falls by \$852.3K overall, and the loss comes mainly from the badge itself: \$696.0K, or about 82%, comes from the direct removal of the badge’s demand boost at fixed prices and fulfillment. Switching adds a comparatively modest loss of \$129.2K. Switching can lower seller surplus in aggregate even though each switch is profitable for the seller who makes it, because it also changes the prices and demand its rivals face. Sellers are worse off mainly because they lose the demand the badge generates, not because the resulting reallocation of fulfillment choices is itself costly.

7 Conclusion

This paper develops and estimates a structural model of Amazon’s marketplace in which the platform sets referral and FBA fees, third-party sellers respond by choosing prices and fulfillment method, and consumers choose among listings with the resulting prices, delivery speeds, and Prime badges. I use the estimated model to evaluate two counterfactual policies motivated by ongoing antitrust scrutiny of Amazon’s practices: decoupling the Prime badge from FBA usage (Seller Fulfilled Prime, or SFP) and removing the Prime badge from the platform entirely.

An important distinction is whether the estimated preference for the Prime badge, β_{Prime} , reflects true utility, such as a genuine service benefit, or only choice utility, such as the badge’s salience. I therefore bound each counterfactual’s consumer welfare effect under both polar interpretations. Removing the Prime badge harms consumers under both interpretations, with joint consumer surplus falling 11.6% under the true-utility interpretation and 3.3% even under the choice-utility one. SFP is close to neutral for joint consumer surplus, raising it by 0.1% under the true-utility interpretation and lowering it by 1.1% under the choice-utility one. That badge removal is robustly harmful while SFP is close to neutral is a useful conclusion precisely because it holds regardless of which interpretation of β_{Prime} is correct.

Seller surplus rises under SFP and falls under badge removal, but through different channels. Under SFP, switching fulfillment method drives roughly 72% of the seller surplus gain, as sellers move from FBA to FBM once Prime no longer requires it. Under badge removal, the loss instead comes mainly from the direct loss of the badge’s demand value at fixed fulfillment choices, with switching a secondary contributor. Finally, relaxing the tie changes Amazon’s incentives in setting its fees. Under SFP, Amazon has an incentive to nearly double the sunscreen referral fee, which leaves sunscreen consumers and sellers worse off even though the policy is close to neutral in aggregate.

These results come from a model that holds fixed the set of sellers on Amazon and the alternatives available to them off the platform. These assumptions suit the question of how conditioning Prime eligibility on the platform's fulfillment service affects third-party sellers and consumers. The framework also lends itself to two natural extensions. First, the model takes sellers' entry decisions as given. Over a longer horizon, changes in Amazon's fees or in the rules for Prime eligibility may change which sellers list on Amazon. Higher fees may lead marginal sellers to exit, while SFP may attract sellers with fast in-house fulfillment. Adding an entry stage, in the spirit of Lee and Musolff (forthcoming), would capture these long-run responses and let the platform's fee choice account for them. Second, the model treats Amazon as the only platform. It captures Amazon's incentives in setting its fees, but not the competition Amazon faces from other sales channels. Sellers can also reach consumers through their own websites or through other marketplaces such as Walmart Marketplace, and these outside options also affect how Amazon sets its fees. The platform's estimated weight on seller surplus may capture part of these considerations in reduced form. Modeling competing platforms explicitly would show how these outside options interact with the incentives identified here. It would also allow the analysis to study how the tie between Prime and FBA affects rival marketplaces and independent fulfillment providers, a concern raised in the FTC's complaint (Federal Trade Commission, 2023).

References

- Allcott, H. (2013). The welfare effects of misperceived product costs: Data and calibrations from the automobile market. *American Economic Journal: Economic Policy* 5(3), 30–66.
- Amazon (2025). \$2.5 trillion in sales and counting: Celebrating 25 years of Amazon’s partnership with independent sellers. <https://www.aboutamazon.com/news/small-business/amazon-independent-sellers-growth-sales>. About Amazon, November 6, 2025.
- Amelio, A. and B. Jullien (2012). Tying and freebies in two-sided markets. *International Journal of Industrial Organization* 30(5), 436–446.
- Anderson, S., S. Sato, and Y. Zenryo (2023). Shipping costs and trading platforms: royalties and input pricing in vertical structures. *mimeo, UVA*.
- Anderson, S. P. and Ö. Bedre-Defolie (2021). Hybrid platform model.
- Anderson, S. P., A. de Palma, and B. Kreider (2001). The efficiency of indirect taxes under imperfect competition. *Journal of Public Economics* 81(2), 231–251.
- Berto Villas-Boas, S. (2007). Vertical relationships between manufacturers and retailers: Inference with limited data. *The Review of Economic Studies* 74(2), 625–652.
- Bonnet, C. and P. Dubois (2010). Inference on vertical contracts between manufacturers and retailers allowing for nonlinear pricing and resale price maintenance. *The RAND Journal of Economics* 41(1), 139–164.
- Bowman, Jr., W. S. (1957). Tying arrangements and the leverage problem. *Yale Law Journal* 67(1), 19–36.
- Bresnahan, T. F. (1982). The oligopoly solution concept is identified. *Economics Letters* 10(1–2), 87–92.
- Brynjolfsson, E., Y. Hu, and D. Simester (2011). Goodbye pareto principle, hello long tail: The effect of search costs on the concentration of product sales. *Management science* 57(8), 1373–1386.
- Brynjolfsson, E., Y. J. Hu, and M. D. Smith (2006). From niches to riches: Anatomy of the long tail. *Sloan management review* 47(4), 67–71.

- Brynjolfsson, E., Y. J. Hu, and M. D. Smith (2010). The longer tail: The changing shape of amazon's sales distribution curve. *Available at SSRN 1679991*.
- Cachon, G. P. and M. A. Lariviere (2005). Supply chain coordination with revenue-sharing contracts: strengths and limitations. *Management science* 51(1), 30–44.
- Cao, S., L. X. Yi, and C. Yu (2024). Competitive bidding in drug procurement: Evidence from china. *American Economic Journal: Economic Policy* 16(3), 481–513.
- Carlton, D. W. and M. Waldman (2002). The strategic use of tying to preserve and create market power in evolving industries. *RAND Journal of Economics* 33(2), 194–220.
- Chevalier, J. and A. Goolsbee (2003). Measuring prices and price competition online: Amazon. com and barnesandnoble. com. *Quantitative marketing and Economics* 1, 203–222.
- Chevalier, J. A. and D. Mayzlin (2006). The effect of word of mouth on sales: Online book reviews. *Journal of marketing research* 43(3), 345–354.
- Choi, J. P. (2010). Tying in two-sided markets with multi-homing. *Journal of Industrial Economics* 58(3), 607–626.
- Choi, J. P., B. Jullien, and Y. Lefouili (2017). Tying in two-sided markets with multi-homing: Corrigendum and comment. *Journal of Industrial Economics* 65(4), 872–886.
- Conlon, C. and J. Gortmaker (2020). Best practices for differentiated products demand estimation with PyBLP. *RAND Journal of Economics* 51(4), 1108–1161.
- Crawford, G. S., R. S. Lee, M. D. Whinston, and A. Yurukoglu (2018). The welfare effects of vertical integration in multichannel television markets. *Econometrica* 86(3), 891–954.
- Crawford, G. S. and A. Yurukoglu (2012). The welfare effects of bundling in multichannel television markets. *American Economic Review* 102(2), 643–685.
- Dana, Jr., J. D. and K. E. Spier (2001). Revenue sharing and vertical control in the video rental industry. *Journal of Industrial Economics* 49(3), 223–245.
- Dranove, D. and G. Z. Jin (2010). Quality disclosure and certification: Theory and practice. *Journal of Economic Literature* 48(4), 935–963.
- Elfenbein, D. W., R. Fisman, and B. McManus (2015). Market structure, reputation, and the value of quality certification. *American Economic Journal: Microeconomics* 7(4), 83–108.

- European Commission (2022). Commission Decision of 20.12.2022, Cases AT.40462 – Amazon Marketplace and AT.40703 – Amazon Buy Box. C(2022) 9442 final. Commitments decision under Article 9 of Regulation (EC) No 1/2003.
- Farronato, C., A. Fradkin, and A. MacKay (2023). Self-preferencing at Amazon: Evidence from search rankings. *AEA Papers and Proceedings* 113, 239–243.
- Federal Trade Commission (2023). Complaint, *Federal Trade Commission et al. v. Amazon.com, Inc.*, No. 2:23-cv-01495 (W.D. Wash.). <https://www.ftc.gov/legal-library/browse/cases-proceedings/1910129-1910130-amazoncom-inc-amazon-ecommerce>. Filed September 26, 2023.
- Fisher, M. L., S. Gallino, and J. J. Xu (2019). The value of rapid delivery in omnichannel retailing. *Journal of Marketing Research* 56(5), 732–748.
- Foros, Ø., H. J. Kind, and G. Shaffer (2017). Apple’s agency model and the role of most-favored-nation clauses. *RAND Journal of Economics* 48(3), 673–703.
- Garland, M. (2023). Amazon reopens Seller Fulfilled Prime enrollment, nixes planned fee. <https://www.supplychaindive.com/news/amazon-reopens-seller-fulfilled-prime-enrollment-no-fee/695976/>. Supply Chain Dive, October 10, 2023.
- Genakos, C. and T. Valletti (2011). Testing the “waterbed” effect in mobile telephony. *Journal of the European Economic Association* 9(6), 1114–1142.
- Genesove, D. and W. P. Mullin (1998). Testing static oligopoly models: Conduct and cost in the sugar industry, 1890–1914. *RAND Journal of Economics* 29(2), 355–377.
- Gutierrez, G. (2021). The welfare consequences of regulating amazon. *Job Market Paper, New York University*.
- Hagiu, A., B. Jullien, and J. Wright (2020). Creating platforms by hosting rivals. *Management Science* 66(7), 3234–3248.
- Hagiu, A., T.-H. Teh, and J. Wright (2022). Should platforms be allowed to sell on their own marketplaces? *RAND Journal of Economics* 53(2), 297–327.
- Hagiu, A. and J. Wright (2015a). Marketplace or reseller? *Management Science* 61(1), 184–203.

- Hagiu, A. and J. Wright (2015b). Multi-sided platforms. *International Journal of Industrial Organization* 43, 162–174.
- He, S. and B. Hollenbeck (2020). Sales and rank on amazon.com. *Available at SSRN* 3728281.
- Ho, J., K. Ho, and J. H. Mortimer (2012). The use of full-line forcing contracts in the video rental industry. *American Economic Review* 102(2), 686–719.
- Hortaçsu, A. and C. Syverson (2007). Cementing relationships: Vertical integration, foreclosure, productivity, and prices. *Journal of Political Economy* 115(2), 250–301.
- Houde, J.-F., P. Newberry, and K. Seim (2023). Nexus tax laws and economies of density in e-commerce: A study of amazon’s fulfillment center network. *Econometrica* 91(1), 147–190.
- Hui, X., M. Saeedi, Z. Shen, and N. Sundaresan (2016). Reputation and regulations: Evidence from eBay. *Management Science* 62(12), 3604–3616.
- Johnson, J. P. (2017). The agency model and MFN clauses. *Review of Economic Studies* 84(3), 1151–1185.
- Jungle Scout (2020). The state of the Amazon seller 2020. <https://www.junglescout.com/wp-content/uploads/2020/02/State-of-the-Seller-Survey.pdf>.
- Kaysen, C. and D. F. Turner (1959). *Antitrust policy: An economic and legal analysis*. Harvard University Press.
- Lai, G., H. Liu, W. Xiao, and X. Zhao (2022). “fulfilled by amazon”: A strategic perspective of competition at the e-commerce platform. *Manufacturing & Service Operations Management* 24(3), 1406–1420.
- Lee, K. H. and L. Musolff (forthcoming). Two-sided markets shaped by platform-guided search. *Econometrica*.
- Li, Z. and G. Wang (2025). Regulating powerful platforms: Evidence from commission fee caps. *Information Systems Research* 36(1), 126–140.
- Luco, F. and G. Marshall (2020). The competitive impact of vertical integration by multi-product firms. *American Economic Review* 110(7), 2041–2064.
- Miller, N. H. and M. C. Weinberg (2017). Understanding the price effects of the Miller-Coors joint venture. *Econometrica* 85(6), 1763–1791.

- Mortimer, J. H. (2008). Vertical contracts in the video rental industry. *Review of Economic Studies* 75(1), 165–199.
- Musolff, L. (forthcoming). Algorithmic pricing, price wars, and tacit collusion: Evidence from e-commerce. *Management Science*.
- Pakes, A., J. Levinsohn, and S. Berry (1995). Automobile prices in market equilibrium. *Econometrica* 63(4), 841–890.
- Posner, R. A. (1978). The chicago school of antitrust analysis. *U. Pa. L. Rev.* 127, 925.
- Raval, D. (2024). Steering in one click: Platform self-preferencing in the Amazon buy box. Working paper.
- Saeedi, M. (2019). Reputation and adverse selection: Theory and evidence from eBay. *RAND Journal of Economics* 50, 822–853.
- Salop, S. C. and D. T. Scheffman (1983). Raising rivals’ costs. *American Economic Review* 73(2), 267–271.
- Shy, O. and Z. Wang (2011, June). Why do payment card networks charge proportional fees? *American Economic Review* 101(4), 1575–90.
- Train, K. (2015). Welfare calculations in discrete choice models when anticipated and experienced attributes differ: A guide with examples. *Journal of choice modelling* 16, 15–22.
- U.S. Postal Service (2023). Introducing USPS Ground Advantage. <https://about.usps.com/newsroom/national-releases/2023/0710-introducing-usps-ground-advantage.htm>. Press release, July 10, 2023.
- Wang, Z. and J. Wright (2017). Ad valorem platform fees, indirect taxes, and efficient price discrimination. *RAND Journal of Economics* 48(2), 467–484.
- Whinston, M. D. (1990). Tying, foreclosure, and exclusion. *American Economic Review* 80(4), 837–859.
- Yu, C. (2024). The welfare effects of sponsored product advertising. *Available at SSRN* 4817542.
- Zhu, F. and Q. Liu (2018). Competing with complementors: An empirical look at amazon.com. *Strategic management journal* 39(10), 2618–2642.

Appendix

A.1 Estimated Sales Quantity

Amazon reports a best-seller rank for essentially every product, but it rarely discloses the quantity sold. This appendix describes how I convert ranks into quantities, following the rank-size approach of Chevalier and Goolsbee (2003) and Brynjolfsson et al. (2006).

Pareto assumption. Within market m in period t , let N_{mt} denote the number of ranked products and let $Rank_{jmt}$ denote product j 's best-seller rank, with rank 1 assigned to the best-selling product. I assume that sales quantities across products follow a Pareto distribution with scale $k_{mt} > 0$ and shape $\theta > 0$:

$$\Pr(Q > q) = \left(\frac{k_{mt}}{q}\right)^\theta, \quad q \geq k_{mt}. \quad (16)$$

A product with rank $Rank_{jmt}$ is outsold by $Rank_{jmt} - 1$ products, so the share of products selling more than it is $(Rank_{jmt} - 1)/N_{mt}$. Equating this empirical share with the Pareto survival function in equation (16) evaluated at the product's quantity Q_{jmt} gives

$$\frac{Rank_{jmt} - 1}{N_{mt}} = \left(\frac{k_{mt}}{Q_{jmt}}\right)^\theta \implies \log Q_{jmt} = \log k_{mt} + \frac{1}{\theta} \log N_{mt} - \frac{1}{\theta} \log (Rank_{jmt} - 1). \quad (17)$$

I approximate $\log(Rank_{jmt} - 1)$ by $\log Rank_{jmt}$, which is accurate for all but the top-ranked products and avoids the undefined case of rank 1. Collecting the market-level terms into a constant and adding an error term yields the standard rank-size relationship

$$\log Q_{jmt} = a - b \log Rank_{jmt} + \varepsilon_{jmt}, \quad (18)$$

where $b = 1/\theta$ and $a = \log k_{mt} + b \log N_{mt}$, which I treat as constant within a category. The error ε_{jmt} captures deviations of individual products from the Pareto benchmark.

Calibration data. For a subset of products, Amazon discloses the number of units bought in the past month (e.g., "100+ bought in past month"), which Keepa records. These disclosed counts are rounded down to coarse bins, appear only for products with at least 50 purchases in the past month, and are available only at the end of the sample period. Let $\mathcal{O}$ denote the set of observations with a disclosed count, and let $\tilde{Q}_{jmt}$ denote the disclosed count, which I treat as the quantity sold. I match each disclosed count to the product's best-seller rank in the same month.

Estimation and prediction. I estimate equation (18) by OLS on the observations in $\mathcal{O}$, with $\tilde{Q}_{jmt}$ in place of Q_{jmt} , separately for each category. I then construct the quantity measure for every observation from its rank:

$$\hat{Q}_{jmt} = \exp(\hat{a} - \hat{b} \log \text{Rank}_{jmt}). \quad (19)$$

This anchors the rank-to-quantity mapping in Amazon’s own disclosed sales figures, while the fitted relationship extends coverage to products and months without a disclosed count. Because the disclosed counts are lower bounds of their bins, $\hat{Q}_{jmt}$ likely understates the level of sales. To the extent that the understatement is similar in proportional terms across bins, it shifts the intercept $\hat{a}$ rather than the slope $\hat{b}$, which governs relative quantities across products. Table 11 reports the estimates. The slope is precisely estimated in both categories. A 1% increase in sales rank (a worse rank) is associated with a 1.29% decrease in quantity for facial sunscreen and a 0.64% decrease for laptops, so sales are more concentrated among top-ranked products in facial sunscreen.

Table 11: Rank-Size Regression Estimates

	Facial Sunscreen	Laptops
$\log \text{Rank}_{jmt}$	−1.294 (0.022)	−0.641 (0.017)
Constant	12.571 (0.115)	8.903 (0.102)
Implied Pareto shape, $\hat{\theta} = 1/\hat{b}$	0.77	1.56
Observations	617	989
R^2	0.85	0.58

Notes: OLS estimates of equation (18) on observations with a disclosed purchase count. The dependent variable is the log of the disclosed number of units bought in the past month. Standard errors in parentheses.

A.2 Computational Implementation

This appendix describes how I compute the seller equilibrium, the derivatives in the platform’s first-order conditions, the GMM estimator, and the counterfactual fees. All computations use Python with NumPy and SciPy, and demand is estimated with pyBLP (Conlon and Gortmaker, 2020). Table 12 collects the numerical settings.

Integration over price sensitivity. I evaluate the integral over the lognormal price coefficient in equation (2) by Gauss–Hermite quadrature with K nodes. Let x_k and ω_k denote the nodes and weights. Consumer type k has price coefficient $\alpha_k = \exp(\mu_\alpha + \sqrt{2} \sigma_\alpha x_k) / \kappa_m$ and weight $w_k = \omega_k / \sqrt{\pi}$, where κ_m is the price normalization used in demand estimation (Table ??). The share of listing j is

$$s_j = \sum_{k=1}^K w_k \frac{\exp(\delta_j - \alpha_k p_j)}{1 + \sum_{g \in \mathcal{J}} \exp(\delta_g - \alpha_k p_g)}, \quad (20)$$

and its demand is $D_j = M_m s_j$, where M_m is the market size of category m . I use 100 nodes for sunscreen. For laptops, where the estimated dispersion in price sensitivity is small, I use 20 nodes in estimation and 100 in the counterfactuals.

Delivery time and fulfillment. Each listing has two delivery times, d_j^P with the Prime badge and d_j^N without it. The delivery time in δ_j is d_j^P if $\text{Prime}_j = 1$ and d_j^N otherwise, so a listing’s mean utility changes with its fulfillment choice. When a listing’s delivery time under its observed status is missing, I draw it at random from listings with the same Prime status. When its delivery time under the other status is missing, I set it to the average among same-brand listings in the market with that status, or to the market average if there are none. In each seller’s own comparison of FBA and FBM, I hold its delivery time at its observed value, so the comparison reflects the badge and the fees but not the change in its own delivery time. Rivals’ inclusive values, market shares, and consumer surplus use the delivery time implied by each listing’s fulfillment choice.

Seller best responses. A seller’s demand depends on its rivals only through the rival inclusive value for each consumer type, $\Lambda_{jk} = \sum_{g \neq j} \exp(\delta_g - \alpha_k p_g)$. Given Λ_{jk} , the share of listing j at price p and Prime status P is

$$s_j(p, P) = \sum_{k=1}^K w_k \frac{\exp(\delta_j(P) - \alpha_k p)}{1 + \exp(\delta_j(P) - \alpha_k p) + \Lambda_{jk}}. \quad (21)$$

A third-party seller solves problems (??) and (??). For each fulfillment method, it maximizes $[(1 - \tau)p - c_j - f_j] s_j(p, P)$ over p by L-BFGS-B on a bounded interval, starting from its current price, where $f_j = \lambda \tilde{f}_j^{FBA}$ under FBA and $f_j = f_j^{FBM}$ under FBM. It then chooses the method with the higher profit. Amazon’s first-party listings use FBA, as they do in the data, and maximize $(p - c_j) s_j(p, 1)$, since referral and FBA fees are transfers within Amazon.

Equilibrium iteration. Every solve starts from the same rule: each seller uses FBA and sets $p_j = 2(c_j + \lambda \bar{f}_j^{FBA})$. In each iteration, all sellers best-respond simultaneously to the current inclusive values. I then update each Λ_{jk} to the average, with equal weights, of its current value and the value implied by the new prices and fulfillment choices. The iteration stops when the mean absolute change in Λ_{jk} falls below a tolerance and no seller changes its fulfillment method. At that point, each seller's price and method are best responses to its rivals' prices and methods, so the solution is a Bertrand–Nash equilibrium of the seller stage.

Equilibrium outcomes. Given equilibrium prices and fulfillment choices in category m and period t , I compute Amazon's first-party profit Π_{mt}^{1P} , its third-party fee revenue R_{mt} , third-party seller surplus, FBA volume, and consumer surplus:

$$\begin{aligned}\Pi_{mt}^{1P} &= M_m \sum_{j \in \mathcal{J}_{mt}^{1P}} s_j (p_j - c_j), \\ R_{mt} &= M_m \sum_{j \in \mathcal{J}_{mt}^{3P}} s_j (\tau_m p_j + FBA_j \lambda_{mt} \bar{f}_{jt}^{FBA}), \\ SS_{mt} &= M_m \sum_{j \in \mathcal{J}_{mt}^{3P}} s_j [(1 - \tau_m) p_j - c_j - f_j], \\ Q_{mt} &= M_m \sum_{j \in \mathcal{J}_{mt}} FBA_j s_j, \\ CS_{mt} &= \frac{M_m}{\bar{\alpha}_m} \sum_{k=1}^K w_k \log \left(1 + \sum_{j \in \mathcal{J}_{mt}} \exp(\delta_j - \alpha_k p_j) \right).\end{aligned}$$

FBA volume Q_{mt} includes first-party listings, since Amazon fulfills those orders too. The factor $\bar{\alpha}_m$ converts utility into dollars. I set $\bar{\alpha}_m = |\bar{\epsilon}_m|/\bar{p}_m$, where $\bar{\epsilon}_m$ is the average own-price elasticity and $\bar{p}_m$ the average price in the estimation sample. Under a lognormal price coefficient, the population mean $\exp(\mu_\alpha + \sigma_\alpha^2/2)$ puts heavy weight on highly price-sensitive consumers who rarely buy. The elasticity-implied $\bar{\alpha}_m$ instead reflects the price sensitivity of the consumers who purchase. The two differ substantially for sunscreen, where $\hat{\sigma}_\alpha = 1.40$, but little for laptops, where $\hat{\sigma}_\alpha = 0.16$. The choice-utility correction in Section ?? uses the same $\bar{\alpha}_m$.

Derivatives. For each category m and period t , I solve the seller equilibrium five times: at the observed fees ($\tau_m, \lambda_{mt} = 1$) and with each fee moved up and down by a fixed step.

For any outcome X_{mt} ,

$$\begin{aligned}\frac{\partial X_{mt}}{\partial \tau_m} &\approx \frac{X_{mt}(\tau_m + \varepsilon_\tau, 1) - X_{mt}(\tau_m - \varepsilon_\tau, 1)}{2\varepsilon_\tau}, \\ \frac{\partial X_{mt}}{\partial \lambda_{mt}} &\approx \frac{X_{mt}(\tau_m, 1 + \varepsilon_\lambda) - X_{mt}(\tau_m, 1 - \varepsilon_\lambda)}{2\varepsilon_\lambda},\end{aligned}\tag{22}$$

for $X_{mt} \in \{\Pi_{mt}^{1P} + R_{mt}, SS_{mt}, CS_{mt}, Q_{mt}\}$. This gives ϕ_{mt} , ω_{mt}^s , ω_{mt}^c , and $\partial Q_{mt}/\partial fee_m$ in equations (??) and (??). The term ϕ_{mt} includes first-party profit with a weight of one. The steps are $\varepsilon_\tau = 0.03$ and $\varepsilon_\lambda = 0.10$ for sunscreen, and $\varepsilon_\tau = 0.01$ and $\varepsilon_\lambda = 0.05$ for laptops. Over two categories and 39 periods, this requires 390 equilibrium solves, all of which converge. These derivatives are computed once and held fixed during estimation.

Moments and estimation. For a candidate b , I compute $Z_{mt}(b)$ in equation (??) using the derivative $\partial Q_{mt}/\partial fee_m$ and the FBA volume Q_{mt} in the equilibrium at observed fees, with g fixed at $\hat{g} = 0.00815$ and $t = 0, \dots, 38$ indexing months from December 2020. Each λ -condition (??) contributes one row per category and period. Each τ -condition (??) contributes one row per category, in which ϕ_{mt} , $Z_{mt}(b)$, ω_{mt}^s , and ω_{mt}^c are each summed over periods. Stacking gives 80 rows. Each A_m enters only its own category's rows, with a coefficient of zero elsewhere. Given b , the sum of squared residuals in equation (??) is minimized by the least-squares regression of ϕ on $(Z_{\text{sunscreen}}(b), Z_{\text{laptop}}(b), -\omega^s, -\omega^c)$, whose coefficients are $(A_{\text{sunscreen}}, A_{\text{laptop}}, \theta^s, \theta^c)$. Let $S(b)$ denote the resulting sum of squared residuals. I obtain $\hat{b}$ by minimizing $S(b)$ over $b \in [0.1, 2]$ with a bounded Brent search, and recover the other four parameters from the regression at $\hat{b}$. All moments are in dollars and receive equal weight.

Inference. The bootstrap treats each month as a block. In each of 2,000 draws, I resample 39 months with replacement, use the same months for both categories, and recompute $\hat{b}$ and the linear parameters as above. Each resampled month keeps its own time index in $e^{\hat{g}t}$, and the τ -rows sum over the resampled months. Standard errors are the standard deviations across draws, and confidence intervals are the 2.5th and 97.5th percentiles. The bootstrap reuses the derivatives from the full sample, so the standard errors condition on the demand and cost estimates and on $\hat{g}$.

Counterfactual fees. In each scenario, I solve the platform's problem (5) for June 2023 at the estimated parameters, with the fulfillment cost evaluated at that month's trend $e^{\hat{g}t}$. Amazon chooses $(\tau_{\text{sunscreen}}, \lambda_{\text{sunscreen}}, \tau_{\text{laptop}}, \lambda_{\text{laptop}})$, and each evaluation of the objective

solves the seller equilibrium in both categories at the candidate fees. Because sellers' fulfillment choices are discrete, the objective is not smooth in the fees, so I maximize it with the Nelder–Mead simplex method rather than a gradient-based method. Candidate fees are projected onto $\tau_m \in [0.01, 0.90]$ and $\lambda_m \in [0.01, 10]$ before each evaluation. The baseline search starts from the observed fees, and each counterfactual search starts from the baseline optimum.

Counterfactual scenarios. Each scenario changes only how Prime status is assigned; the solver is otherwise unchanged. Under SFP, a listing qualifies if its delivery time without FBA satisfies $d_j^N \leq 2$. A qualifying listing carries the badge under either fulfillment method, but pays the FBA fee only under FBA and keeps its own delivery time under FBM. Non-qualifying listings carry the badge only under FBA. Under No Prime, $Prime_j = 0$ for all listings, while delivery time still depends on fulfillment. The decomposition in Table 10 adds three steps in sequence. The badge step applies the new eligibility rule at the baseline prices, fees, and fulfillment choices, and recomputes shares and surplus without re-solving the equilibrium. The fee and price step sets the fees to the scenario's optimum and re-solves prices, with each seller's fulfillment method fixed at its baseline choice. The switching step re-solves the full equilibrium at the same fees, so that sellers can also change fulfillment method.

Table 12: Numerical Settings

	Sunscreen	Laptops
<i>Seller equilibrium</i>		
Quadrature nodes K	100 / 100	20 / 100
Price normalization κ_m	10	200
Price search interval (\$)	[0.01, 200]	[1, 5,000]
Market size M_m	10^7	10^8
Weight on new inclusive values	0.5	0.5
Convergence tolerance	5×10^{-4} / 10^{-4}	5×10^{-4} / 10^{-4}
<i>Derivatives and estimation</i>		
Observed fees (τ_m, λ_{mt})	(0.15, 1)	(0.08, 1)
Step size ε_τ	0.03	0.01
Step size ε_λ	0.10	0.05
Search interval for b	[0.1, 2]	
Cost trend $\hat{g}$ (per month)	0.00815	
Bootstrap draws	2,000	
<i>Counterfactual fees</i>		
Bounds on τ_m / λ_m	[0.01, 0.90] / [0.01, 10]	
Nelder–Mead tolerance / maximum iterations	0.005 / 600	

Notes: Where two values are separated by a slash in the seller-equilibrium rows, the first applies to estimation and the second to the counterfactuals. The convergence tolerance applies to the mean absolute change in the rival inclusive values Λ_{jk} between iterations; an equilibrium also requires that no seller change its fulfillment method. The price normalization follows Table ??.