The Effects of Service Integration on Platform Competition and Welfare: Evidence from Fulfillment by Amazon

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Abstract

I study the welfare effects of digital platform's vertical integration of services, such as e-commerce logistics—Fulfillment by Amazon. Integration may benefit or harm consumers and sellers. On the negative side, the integrated platform lets its service be exclusive to (or favor) the platform's own marketplace, drawing consumers and sellers away from rival platforms and hence weakening cross-platform competition. However, on the positive side, the integrated platform has an incentive to lower service fees to increase within-platform sales and commission profits. I develop an empirical framework to evaluate these welfare effects and apply it to logistics integration in the U.S. e-commerce markets of Amazon and Walmart. I construct a novel dataset by linking product and seller data across the two platforms. I first estimate a regression discontinuity design using Amazon's logistics fee schedule and show that sellers on Amazon who face higher fees are less likely to use Amazon logistics and more likely to join Walmart and raise prices on Amazon. I then build an equilibrium model to quantify platform's pricing incentives and the welfare effects. In my model, consumers buy a product across platforms, and sellers choose prices, platforms to enter, and logistics to use. Accounting for responses of consumers and sellers, Amazon and Walmart engage in duopoly competition by setting logistics fees and commission rates while setting own product prices. The estimates show that Amazon substantially lowers logistics fees to protect commission profits. I find that separating Amazon logistics reduces consumer and seller welfare by raising both logistics fees and commission rates and increasing consumer prices. In addition, the presence of competing platform strengthens the downward pricing pressure on logistics fees. As a policy direction, I argue that interoperability of integrated logistics can improve consumer and seller welfare.

Keywords: vertical integration, digital platforms, antitrust, e-commerce, logistics

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1 Introduction

Digital platforms increasingly integrate complementary services into the marketplaces mediating consumers and sellers. Amazon is a prominent example. Beyond being the dominant e-commerce platform, Amazon delivered 6.7 billion packages to United States households in 2025,[1] exceeding the parcel volumes of USPS, UPS, and FedEx and becoming the nation's largest logistics provider (Gürbes, 2026).[2] Fulfillment by Amazon (FBA) is a major part of Amazon logistics, through which Amazon stores and delivers sellers' products in exchange for logistics fees. In fact, Amazon logistics is one example of widespread vertical integration of services by platforms. Walmart and TikTok also operate their own e-commerce logistics while Google and Apple provide payment systems for app developers alongside their app marketplaces.

Platform service integration has become an important subject of antitrust debate, including *FTC v. Amazon* (2023) and *Epic v. Google* (2025), in which regulators have focused on two potential concerns. The first issue is excessive fee charges. Regulators are worried that these platforms are so large that they exploit their market power by charging high fees for the integrated service, which leads to welfare losses. The second issue is lock-in because the integrated service can hinder users' cross-platform activity. For instance, when sellers use Amazon logistics, Amazon stores sellers' products in Amazon's facilities, which may make it more difficult for sellers to use the same inventory to fulfill orders from competing platforms.

Motivated by these regulatory concerns, in this paper, I address the welfare questions: does a platform's service integration benefit or harm consumers and sellers? Through what economic channels does the integrated service create gains and losses, and what policies would improve market welfare? I clarify the economic forces that such integration creates and develop an empirical framework to evaluate its welfare effects. I apply this framework to logistics integration in the e-commerce competition between Amazon and Walmart.[3] This application is timely, as the welfare effects of Amazon logistics are the central to the ongoing federal antitrust case, *FTC v. Amazon* (2023), and also a key focus of global regulators (AGCM, 2021; EC, 2022; CMA, 2023).

A platform's service integration brings a welfare-trade off. On the positive side, the quality of the integrated service is often high (e.g., Amazon Prime shipping). Moreover, because the platform earns commissions on sellers' revenue, it has an *commission incentive* to set low service fees to promote sales within its marketplace and increase commission profits. On the negative side, the platform lets its integrated service be *exclusive* to (or favor) the platform's own marketplace. This exclusivity (or, asymmetry) draws consumers and sellers away from rival platforms, thereby weakening cross-platform competition. Furthermore, sellers who adopt the service may face increase in costs to enter

[1] This number is equivalent to 18.3 million per day and 212 per every second.

[2] This volume surpasses that of USPS (6.6 billion), UPS (4.4 billion), and FedEx (3.6 billion) (Gürbes, 2026).

[3] Amazon is the dominant platform (40% market share) and Walmart is second (10%). These are the only two marketplaces with shares above 4%.

a rival platform, which weakens the cross-platform competition. Both weakened competition and quality differentiation allow the integrated platform to add a markup to its service fees—a pricing incentive offsetting the commission incentive.[4]

The core welfare tension of platform service integration resembles the classical trade-off in the theory of vertical integration: foreclosure to rivals to divert sales into the integrated firm (Salop and Scheffman, 1983; Salinger, 1988) against the elimination of double marginalization through internalizing both downstream and upstream profits (Spengler, 1950). What is unique about a platform industry is that platforms compete against each other *indirectly* through equilibrium responses of consumers and sellers. Cross-platform substitution of consumers and sellers, and how the integrated service affects this substitution are therefore essential margins that determine the net welfare outcomes, posing a challenge on empirical research as data on cross-platform behavior are rare.

To address this theoretical ambiguity and practical challenge, I construct a novel dataset on Amazon and Walmart that sheds light on the competitive pressure that Amazon faces from a rival platform—an important margin that is understudied (Lee and Musolff, 2025). To examine cross-platform behavior of consumers and sellers, I link product and seller data across the two platforms and observe sellers' platform participation, prices, logistics choices, sales ranks and other rich characteristics on both platforms.

There are two main parts in the dataset. The first is the *full-category panel*. I match products across platforms using universal product codes (UPCs) and link sellers through business names, addresses, and phone numbers. The resulting panel tracks prices and logistics choices for approximately 100,000 bestsellers across nine product categories on Amazon, and verify entry of products and sellers into Walmart, from January 2021 through August 2025. The second is the *kitchen appliance panel*, a more detailed panel covering bestsellers within a kitchen appliance category on both Amazon and Walmart from April to June 2025. This panel's focus—kitchen appliance category—is well suited to the empirical analysis about logistics services as the diverse sizes and weights of kitchen appliances generate substantial variation in logistics fees. The panel records rich product characteristics on *both* platforms. I augment the kitchen appliance panel by using Numerator consumer panel containing information on consumers' income and platform-specific membership status (i.e., Prime and Walmart+) and their shopping behavior across retails including the two platforms. My dataset also contains logistics fees and commission rates that each seller pay to the platforms, taking large portions of sellers' costs, as they are publicly announced menu by Amazon and Walmart.

I first use the full-category panel and document descriptive facts about the cross-platform competition between Amazon and Walmart. The first fact is that majority of Amazon sellers use

[4]Given the net effect, division of welfare between consumers and sellers depends on the degree of sellers' fee pass-through to consumers.

Amazon logistics, indicating some profitable reasons to use. Second, multihoming—joining both platforms—is rare among Amazon sellers. This implies non-negligible entry costs into Walmart. I also report that Amazon sellers tend to store all or none of their products for Amazon logistics, implying logistics choice is made at seller-level and benefits of pooling inventory. In addition. I document that there is a monotonically increasing relationship between the number of products on Amazon and the likelihood of joining Walmart *only for* Amazon sellers who use independent logistics instead of Amazon logistics. This evidence is consistent with benefits of inventory pooling across platforms, and Amazon logistics usage may negatively affect scale benefits that sellers can leverage.

To further attain evidence, I exploit discontinuities in Amazon's logistics fee schedule: products are assigned to tiers by size and weight, and fees jump by 30—50% at tier thresholds. Using a regression discontinuity design, I find that products just above a threshold are about half as likely to be fulfilled by Amazon and more than twice as likely to be sold on Walmart by the same seller. Sellers pass the higher fees through to consumer prices on Amazon, with greater pass-through among those using Amazon's logistics. This means that Amazon logistics effectively affects cross-platform competition through sellers' multi-platform activity and consumer prices as well.

I then build an equilibrium model to quantify platform's pricing incentives and the welfare effects. On the demand side, consumers buy a product across platforms, with heterogeneous valuations of prices, logistics, and platforms. The valuations are interacted with demographic types of consumers such as income level and platform membership subscriptions. [5] On the supply side, sellers choose prices, platforms to enter, and logistics to use, considering the demand and cost-side impacts of these choices. The main determinants of a seller's marginal costs are logistics fees and economies of scale. If a seller uses integrated logistics, they pay posted fee schedules but cannot pool inventory across platforms, leading to a loss of effective scale. In contrast, if a seller uses independent logistics, they pay similar fees—proxied by UPS fees—but can pool inventory across platforms to attain further scale. Sellers also incur fixed costs to join platforms, which are a function of their logistics choice. These fixed costs absorb cost-side (dis)advantages not captured by variable costs, thereby rationalizing sellers' observed entry and logistics decisions. Accounting for equilibrium responses of consumers and sellers, Amazon and Walmart engage in duopoly competition by setting logistics fees and commission rates while also competing as own-product retailers.

I estimate the empirical model as follows. Demand parameters are estimated using a combination of aggregate and micro-level moment conditions (Petrin, 2002; Berry *et al.*, 2004; Berry and Haile, 2024). To address the endogeneity of prices, I use logistics fees as an instrument. The

[5] To be specific, consumers choose among differentiated products across Amazon and Walmart, with integrated logistics entering as a product characteristic and platform dummies defining the substitution nests. I interact Amazon logistics with Prime subscription to capture the demand-side benefit a seller obtains from Prime eligibility, and allow for random coefficients and demographic interactions so that demand curvature—which governs pass-through—is captured in a flexible way (Weyl and Fabinger, 2013; Miravete *et al.*, 2023)

fees are excluded from the utility specification, yet provide exogenous variation in prices as a cost-shifter. Marginal costs are recovered from the first-order conditions of sellers' pricing, and I use rival products' excluded demand shifters as instruments for the endogenous scale variable.[6] Fixed costs are identified from revealed-preference inequalities on entry and logistics decisions, as in Eizenberg (2014); Pakes *et al.* (2015). I set up a linear programming problem to implement a moment-inequalities estimator. The main variation comes from sellers' observed logistics and entry choices because the fixed costs rationalize those decisions while accounting for the variable profit of each. For estimation, I use the kitchen appliance panel augmented with Numerator consumer panel that contain rich characteristics on both platforms.

The demand estimates show that consumers are price sensitive, indicated by an average own-price elasticity of -4.2.[7] The degree of sensitivity varies by income and membership type. In addition, Amazon Prime subscribers substantially benefit from Amazon logistics, with a willingness to pay a premium of approximately 12% of prices (on average $8 per shipment) for Amazon logistics products over independent logistics. Therefore sellers are strongly incentivized to use Amazon logistics, as the majority of U.S. households subscribe to Amazon Prime (80%). The estimated quality of Walmart logistics, however, is not high enough to pull consumers away from competitors. Lastly, membership subscriptions sort consumers onto different platforms, and the nesting parameter indicates statistically significant yet modest within-platform substitution, holding other attributes fixed.

The cost estimates reveal that integrated logistics charges lower fees but induces a significant loss of scale through inventory fragmentation. Both Amazon and Walmart logistics fees are generally below the estimated fees of independent logistics. Therefore, sellers have strong incentives to adopt Amazon logistics together with the demand-side premium of using Amazon logistics: for a single-homing Amazon seller, using Amazon logistics raises estimated monthly variable profit by 60% above the variable profit under independent logistics. This gap rationalizes the high adoption of Amazon logistics. Using an integrated logistics, however, also brings a cost-side penalty because of significant economies of scale: 1,000 additional sales reduce marginal cost by $0.144 per unit, implying $750 variable cost savings per product on average. Holding all else fixed, inventory fragmentation therefore weakens the incentive to multihome by reducing this scale benefit. In addition, the fixed-cost estimates show that sellers who use Amazon logistics face substantially large fixed cost of joining Walmart, ranging from $33,000 to $77,000. As the majority of sellers in the Amazon marketplace use Amazon logistics, these estimates of scale economy and fixed costs rationalize the low multihoming rate of Amazon sellers.

Using the estimated demand and cost functions, I measure platforms' pricing incentives of logistics fees and commission rates. I first decompose the first-order condition for the logistics fee into

[6] To be specific, rival characteristics affect the scale variable through the demand-side channel, and are therefore excluded from the marginal cost function, and exogenous to unobserved marginal-cost shocks.

[7] This estimate is consistent with the ranges reported in the literature (Yu, 2024; Farronato *et al.*, 2026).

four terms: logistics cost, markup, the commission incentive, and retail diversion. Logistics cost is the per-unit cost of processing logistics operations, and the markup is the inverse of the semi-elasticity of sellers' demand for integrated logistics with respect to the logistics fee. The commission incentive measures the decrease in commission profits relative to the decrease in logistics quantity when the logistics fee rises; it is expected to be negative because logistics services and within-platform sales are complements. Retail diversion measures the increase in the platform's own retail profit relative to the increase in logistics profit when the logistics fee rises; it captures the platform's incentive to raise competing sellers' costs within its own marketplace, a classic raising-rivals'-costs mechanism from the vertical integration literature. The estimates show that both platforms can exert substantial market power through the logistics channel: with the logistics fee normalized to a unit value, the markup term is 0.64 on Amazon and 0.43 on Walmart. This markup, however, is largely offset by the commission incentive to foster within-platform sales and protect commission profits (-0.35 and -0.41, respectively). The estimates of retail diversion terms are small relative to other terms. Commission rate pricing is analogous to logistics fee pricing, although the markup term mostly explains the pricing unlike logistics fees.

To measure the welfare effects of vertical integration, I simulate vertical separation of Amazon logistics and compare the welfare outcomes to the current regime. This simulation shows that such a separation leads to a consumer welfare loss by 31.6%. The independent FBA and the Amazon marketplace will independently charge logistics fees and commission rates, leading to dual increases in both fees (48.3%) and rates (11.0pp). This occurs because the countervailing forces that generate strong downward pricing pressure on both have been removed. Overall, logistics integration is beneficial for consumers, even though the pro-competitive margins of separation, such as multihoming, non-exclusive quality, and inventory pooling, work. Separation raises logistics fees and commission rates by enough to offset these gains, and benefits Walmart substantially.

Although I find welfare gains from Amazon's logistics integration, this does not imply that no policy intervention can further improve market welfare. Using the estimated model, I show that a policy mandating full interoperability of the integrated logistics can improve social welfare. Full interoperability means that a seller can use the integrated logistics to fulfill orders from a competing platform with the same quality, fees, and fixed costs of entry across platforms. The counterfactual simulation of full interoperability increases consumer and seller welfare by 31.7% and 18.5%, respectively. A decomposition indicates that enforcing cost-side interoperability yields larger welfare gains than removing the exclusive quality. Enforcing interoperability is a feasible intervention because logistics quality and fees are objectively measurable and verifiable. This result supports the active enforcement of interoperability obligations by European regulators under the Digital Markets Act (European Union, 2022).[8]

[8] Article 6(7) of the DMA mandates designated gatekeepers to grant third parties free and effective interoperability with hardware and software features that the gatekeepers reserve for their own services. The European Commission has opened specification proceedings to implement this obligation against Apple (March 2025) and Google (January

To quantify the extent to which a competing platform disciplines the dominant platform's pricing, I simulate a counterfactual that removes the Walmart marketplace and its logistics service and makes Amazon be a monopolist. Without the rival, Amazon raises its logistics fee by 40.6% and its commission rate from 15% to 19.3%, average prices rise by 8.7%. Overall welfare falls by 15.4%, with consumer welfare down 38.6% and seller profits down 23.6%, while Amazon gains 45.5%. These results show that a rival platform substantially constrains the dominant platform's charges, and that removing it transfers surplus from consumers and sellers to the platform. The simulation also speaks to recent ruling that introduce platform competition. In *Epic v. Google* (2025), the court ordered Google to open the Android app market to rival app stores—a market that shares the structure studied here, with an integrated payment service in place of logistics. My estimates suggest that such an entry-enabling remedy can generate large consumer and seller gains by restoring the competitive pressure that disciplines the integrated platform's fees and commissions.

Related Literature The main contribution of this paper is developing and estimating a framework to evaluate the *cross-platform* competitive and welfare effects of vertical integration in multi-sided markets with a timely application to Amazon and Walmart markets.

To the best of my knowledge, this research is the first attempt to develop a model that examine the multi-platform behavior of consumers and sellers on the Amazon and Walmart marketplaces, as well as the competition between them. Moreover, it provides credible evidence on the effects of sellers' adoption of Amazon logistics on both within- and cross-platform market outcomes using a regression discontinuity design. Several papers study vertical integration *within* the Amazon marketplace, mainly focusing on not the logistics integration but Amazon's dual role as an own-product retailer and intermediary. Specifically, existing literature investigates self-preferencing in search and recommendation algorithms (Chen and Tsai, forthcoming; Lam, 2021; Farronato *et al.*, 2023; Reimers and Waldfogel, 2023; Waldfogel, 2024; Lee and Musolff, 2025), the welfare effects of sponsored advertisements (Yu, 2024), and the impact of private brand products (Farronato *et al.*, 2026).[9]

This research highlights cost-side entry frictions generated by vertically integrated services in platform markets, which contributes to the broader literature on competition in multi-sided markets. The novelty of this research comes from endogenizing both the use of integrated services and multi-platform entry decisions, and quantifying the the frictions of the integration. Theory suggests that multihoming is an essential economic behavior for facilitating competition among platforms (Armstrong, 2006; Bakos and Halaburda, 2020; Teh *et al.*, 2023). However, few empirical studies incorporate both platform pricing and two-sided multihoming; notable exceptions include Wang

2026).

[9] One paper that sheds light on cross-platform competition is Farronato *et al.* (2026). They document the limited effects of hiding Amazon's own private brands from search results on consumers' cross-platform search behavior. This research complements their analysis by expanding the scope of the structural analysis to include duopoly competition between Amazon and Walmart.

(2025) on the U.S. payment industry and Sullivan (forthcoming) on the U.S. food delivery industry.

This research is also related to the papers on the welfare effects of vertical integration. I contribute to this literature by empirically examining the equilibrium effects of vertical integration in *platform markets*. Most of the papers study the vertical integration under standard input-output supply chain. Theory predicts both pro- and anti-competitive effects of vertical integration (Spengler, 1950; Williamson, 1971; Salop and Scheffman, 1983; Hart and Tirole, 1990), highlighting the tension between efficiency gains and foreclosure (i.e., raising rival's costs) incentives.[10] Along with the increase in regulatory attention on vertical integration since 1984 merger guildeline, there are growing number of papers empirically examining the welfare effects of it (Hortaçsu and Syverson, 2007; Crawford *et al.*, 2018; Luco and Marshall, 2020; Hodgson and Sun, 2025). The literature provides mixed evidence on vertical integration; see Beck and Scott Morton (2021) for comprehensive survey.

This research also contributes to the literature on economies of scale and retail competition by examining those of e-commerce independent sellers, factors driving their logistics and cross-platform behaviors. Economies of scale (or density) have been a key economic force for retail competition (Jia, 2008; Holmes, 2011), as they bring substantial cost-side advantages.[11] The most relevant paper to this research is Houde *et al.* (2023) that estimates the economies of density for Amazon and show the distortionary effects of the nexus tax law on fulfillment expansion choices. On top of their findings on substantial gains to Amazon's logistics integration, I examine whether such gains are indeed distributed consumers and sellers, and its cross-platform competition effects accounting for equilibrium responses of market participants.

2 Institutional Background

I study e-commerce platform markets in the U.S., where the platforms, Amazon and Walmart, operate an integrated logistics service for sellers who sell products through a platform's marketplace. This subsection describes the market structure, the role of logistics in e-commerce, and the key features of the two integrated services.

2.1 Market Structure

The U.S. e-commerce industry is highly concentrated. In 2024, Amazon recorded \$447.5 billion in sales revenue, capturing 39.7% of the market, while Walmart recorded \$120.9 billion, accounting for

[10] The elimination of double marginalization (Spengler, 1950) and the alignment of investment incentives (Grossman and Hart, 1986; Ciliberto, 2006; Yang, 2020) are highlighted as key pro-competitive benefits of vertical integration. Conversely, literature on vertical foreclosure underscores the potential for integrated firms to harm rivals. Early theoretical work focuses on input foreclosure, where an integrated upstream firm restricts supply or raises costs for downstream competitors (Salop and Scheffman, 1983; Salinger, 1988; Ordover *et al.*, 1990).

[11] Jia (2008) analyze competition between large discount retailers, such as Walmart and Kmart, and smaller local retailers by building structural entry models that capture economies of scale. Holmes (2011) estimate the economies of density arising from the geographic proximity of Walmart's distribution centers.

10.6% (Digital Commerce 360, 2025). The gap between these two and the other platforms are large; no other U.S. e-commerce marketplace exceeds a 4% market share according to an industry report (eShipz, 2026). These statistics imply that Amazon and Walmart are effectively main competitors to each other in the e-commerce market. This institutional fact motivates me to model marketplace competition as a duopoly between Amazon and Walmart. Despite the two being the major players in e-commerce markets, the two platforms differ in seller participation: Amazon hosts approximately 2 million active independent sellers (Seller Labs, 2025; Red Stag Fulfillment, 2026), compared to approximately 200,000 on Walmart (Red Stag Fulfillment, 2025) in 2025.

The two platforms' core business is marketplace intermediation: each connects consumers with sellers and charges sellers a referral commission proportional to the price of each sale (i.e., ad-valorem). These commission rates have been unchanged and stable for a long-period. In the marketplace, a seller lists products on one or multiple marketplaces, and sets its own product prices. Consumers visit online shop, compare listed products and choose among them.

In addition to intermediation, both platforms are vertically integrated into further stages of the e-commerce supply chain. First, each functions as a logistics provider that offers logistics services to sellers. Second, each acts as an own-product retailer—also known as a first-party retailer—that sells products directly to consumers. Together with the intermediation, these roles define a platform's payoff: each platform earns commission revenue from total independent sellers' sales, logistics profits from sales processed by the integrated logistics, and own-product retail profits by selling products. Therefore, platform charges three broad categories of prices: commission rate, logistics fees, and own product prices, and each pricing reflects its impacts on the other profit margins.

2.2 E-commerce Logistics

E-commerce sellers use a logistics (or fulfillment) service to store inventory and deliver products to consumers after an order is placed. A logistics service therefore combines two main functions: warehousing, in which sellers hold inventories of their products, and shipping, in which individual orders are picked, packed, and delivered to consumers. Logistics providers differ in service quality, including shipping speed and reliability, while logistics fees typically depend on product weight and size. These features make sellers' logistics choices relevant for both the cost of serving consumers and the quality of the purchasing experience.

An important feature of e-commerce logistics is the presence of economies of scale from pooling inventory. A seller operating on multiple marketplaces can, in principle, use a single logistics provider to serve orders originating from each platform. Doing so allows the seller to maintain a common inventory pool rather than splitting inventory across multiple logistics services. Pooling can reduce operational costs and allow sellers to benefit from volume discounts.[12] Consistent with these incentives, the FTC notes that many sellers would prefer to use a single fulfillment provider

[12] Examples are shown in Figure A10

for their orders both on and off Amazon(*FTC v. Amazon* (2023)). Thus, the ability of a logistics provider to serve multiple marketplaces can directly affect the cost of multihoming and therefore cross-platform selling.

2.3 Platform's Integrated Logistics

Amazon operates its own fulfillment service, FBA, alongside its online marketplace.[13] This vertical integration links sellers' logistics decisions to their choice of marketplace. Although sellers using FBA may use Amazon's logistics to fulfill orders originating outside Amazon when such logistics is permitted, these orders face less favorable terms than within Amazon orders.[14] To be specific, Amazon charges higher fees on orders from competing marketplaces. Sellers may therefore choose a separate logistics provider for sales on a competing marketplace. Maintaining multiple logistics services increases the cost of operating across platforms. This practice also requires sellers to split inventory across logistics service, thereby sellers losing some of the economies of scale associated with inventory pooling. These cross-platform logistics frictions can consequently affect sellers' incentives to multihome and, in turn, competition between marketplaces.

At the same time, integration gives FBA an important demand-side advantage on Amazon. FBA gives sellers access to Amazon's Prime shipping service, which is available to Prime subscribers on the Amazon marketplace.[15] Because Prime eligibility can make an offer more attractive to consumers, sellers may have an additional incentive to adopt FBA in order to obtain this higher-quality fulfillment service and increase sales on Amazon.[16] The value of FBA to a seller therefore reflects both its logistics costs and the demand benefits associated with Amazon's integrated marketplace and logistics services. This combination of demand-side benefits and cross-platform logistics frictions is central to understanding how fulfillment integration affects sellers' logistics and marketplace choices.

Walmart also operates an analogous service, Walmart Fulfillment Service (WFS), which functions similarly to FBA in its basic operations, yet WFS is not tightly tied to a demand-side member-

[13] Amazon does not separately disclose FBA revenue. In 2024, its "Third-party seller services" segment, which bundles referral commissions with FBA fulfillment and shipping fees, generated \$156.2 billion, roughly 63% the size of Amazon's \$247.0 billion first-party online stores business (Amazon.com, Inc., 2025). Given that 82% of active Amazon sellers use FBA (Red Stag Fulfillment, 2026), FBA accounts for the majority of this segment.

[14] Walmart's Shipping and Fulfillment Policy prohibited the use of Amazon's fulfillment for Walmart orders until May 15, 2025. Almost the entire sample period of my dataset predates the chage in Walmart's policy on Amazon logistics.

[15] Fast shipping of Amazon logistics is also documented in the literature (Edgel *et al.*, 2023; Etumnu and Foster, 2026).

[16] Amazon runs a program called Seller Fulfilled Prime (SFP) that allows sellers to use independent logistics and be Prime eligible, conditional on passing a one-month performance evaluation. Amazon resumed SFP in October 2023 after a multi-year suspension. In practice, SFP participation, however, is negligible: in my data, fewer than 1% of sellers use independent logistics and hold Prime status. The ex-post assessment requirement—under which a seller must operate without Prime during a trial period before potentially earning the badge—likely discourages adoption, particularly when the demand benefits of Prime are large. This is because independent sellers have to give up Prime-induced revenue gains for at least a month, which can be regarded as costs to pay to attain SFP. I therefore treat FBA as effectively the only route to be Prime eligible on Amazon.

ship program, Walmart+. WFS orders ship within two business days regardless of whether the consumer subscribes to Walmart+, and non-members also receive free shipping on orders above \$35. Therefore, adopting Walmart logistics confers a smaller incremental demand advantage than adopting Amazon logistics does.

Logistics fees on both platforms are publicly posted. Specifically, Amazon calculates the per-unit shipping fee (called the "fulfillment fee") in two steps. First, it assigns each product to a *size tier* based on sizes and shipping weight. Second, within each tier, it applies a fee schedule under which fees increase monotonically with shipping weight. Notably, fees jump discretely at size-tier boundaries: a product that exceeds a tier threshold is assigned to the larger tier and face substantially higher fees. I describe the details of these fee schedules and exploit these discontinuities in a regression discontinuity design in Section 3.3.1.

3 Data and Evidence

3.1 Data

For descriptive and RD analyses, I first study bestsellers on the Amazon marketplace across broad categories, while verifying the presence of products and sellers on Walmart. I call this dataset covering broad products as "full-category panel." For the analysis of model estimation and counterfactual analyses, I focus on the kitchen appliances category and construct the dataset covers rich characteristics on both platforms. I refer to this as the "kitchen appliance panel." I augment the two main panels with the Numerator consumer panel that shows consumers multi-retail shopping behavior with their income and membership subscriptions information.

full-category panel I build the full-category panel as follows. I obtain the bestseller lists in nine broad Amazon categories, covering approximately 100,000 products.[17] For each product, I collect historical product and seller characteristics from Keepa. I then determine whether the product is listed on Walmart using UPC identifiers and attain the corresponding Walmart-side characteristics from two data services, DataSpark and BlueCart. I match sellers across platforms on display name, business name, address, and phone number. The panel spans January 2021 to August 2025 on the Amazon side and January 2021 to April 2024 on the Walmart side.[18] Appendix Section B describes the construction in detail, and Table A2 summarizes the data sources.

Table 1 reports summary statistics at two levels of aggregation: a monthly product panel and a monthly seller panel. FBA is the dominant logistics choice among independent sellers: 67% of products have at least one FBA seller, and 61% of sellers primarily use FBA. The average FBA fee

[17] The categories are Appliances, Electronics, Office Products, Tools & Home Improvement, Home & Kitchen, Sports & Outdoors, Pet Supplies, Beauty & Personal Care, and Clothing, Shoes & Jewelry. I retrieve bestsellers at two points in time, April 2024 and August 2025.

[18] The asymmetry of data period reflects the end of the service by the data provider DataSpark.

Table 1: Summary Statistics of the full-category panel

Variables	Mean	SD	Observations
Panel A: Monthly-product			
Price ($)	55.97	106.23	1,599,657
FBA fee ($)	7.83	13.76	1,589,115
Shipping weight (lb)	7.03	27.32	1,479,075
Has FBA seller	0.67	0.47	1,599,657
Has non-FBA seller	0.36	0.48	1,599,657
Has multihoming seller	0.08	0.27	849,250
Panel B. Monthly-seller			
Products offered	4.17	47.89	1,557,204
FBA seller	0.61	0.49	1,557,204
Multihomes	0.02	0.15	1,066,053

Notes. Summary statistics for the monthly product panel (Panel A: ASIN-by-month, 2021–2025; 1,599,657 product-months, 106,583 ASINs) and the monthly seller panel (Panel B: 1,557,204 seller-months, 185,683 sellers). Sellers refer to independent sellers. Prices include shipping charges. *Has multihoming seller* and *Multihomes* are defined on the Walmart-matching subsample (849,250 product-months; 1,066,053 seller-months). *FBA seller* equals one if at least half of a seller's products use FBA; *Multihomes* equals one if the seller lists any product on Walmart.

is $7.8 per unit, and the typical product weighs about 7 pounds. Within the subsample matched to Walmart, 7.6% of products have a multihoming seller, and an estimated 2.3% of sellers list any product on Walmart in a given month.[19]

Kitchen appliance panel I additionally construct the panel, which complements the full-category panel with richer product characteristics, especially logistics service usage and sales estimates on the Walmart side. I focus on the kitchen appliance category that has several advantages for the structural analysis. First, kitchen appliances, such as air fryers and microwave ovens, offer large variation in product weights and sizes, and thus in logistics fees. Second, sellers in this category multihome at non-trivial rates between Amazon and Walmart, and these rates are comparable to those in the full-category panel. In addition, products are differentiated primarily on observable physical characteristics, which simplifies the demand model and allows me to focus on the role of logistics services.

I take weekly snapshots of bestsellers of each subcategory in the kitchen appliance category to assemble the appliances panel and aggregate them at monthly-level.[20] I scrape approximately 140 bestsellers on Amazon and 40 on Walmart each week simultaneously. I also collect similar numbers of featured products on the platforms, to obtain information about organic search ranks. In addition

[19]These low rates partly reflect the size difference between the two seller bases: Walmart hosted roughly 150,000 sellers in 2024, about 7.5% of the active Amazon seller base (Red Stag Fulfillment, 2026).

[20]There are 13 subcategories in the kitchen appliance category. These are coffee makers, bread machine, air fryers, blender, electric skillets, food processor, kettle, waffle irons, hand mixers, electric pressure cookers, food steamers, microwave ovens, electric grill.

to bestseller ranks on the scraped data, I use two data services, JungleScout and Bizmetrica, to get the sales estimates as a proxy for sales.[21] I match products and sellers based on UPC and seller identifiers, which is similar to constructing the full-category panel. I explain details of the data construction in the Appendix Section B.

Table 2: Summary Statistics of kitchen appliance panel

Platform	Amazon			Walmart		
Logistics	All	FBA	Independent	All	WFS	Independent
Sales	2751.2	2841.1	2022.2	3114.5	3035.2	3411.8
	(5265.1)	(5407.3)	(3852.2)	(8051.7)	(7547.5)	(9720.8)
Price ($)	75.9	70.2	121.9	65.7	57.9	95.0
	(84.2)	(79.1)	(107.1)	(59.0)	(46.5)	(85.7)
FBA/WFS	0.89	1.00	0.00	0.79	1.00	0.00
	(0.31)	(0.00)	(0.00)	(0.41)	(0.00)	(0.00)
Shipping weight (lb)	12.7	11.7	21.3	11.9	10.5	17.2
	(15.2)	(13.8)	(21.5)	(14.2)	(12.1)	(19.5)
FBA/WFS fee ($)	13.1	12.3	19.0	9.6	11.8	16.4
	(10.6)	(9.5)	(15.6)	(6.3)	(8.1)	(14.1)
Platform Own Retail	0.27	0.31	0.00	0.39	0.50	0.00
	(0.45)	(0.46)	(0.00)	(0.49)	(0.50)	(0.00)
Observations	4529	4032	497	1458	1151	307

Notes. Each cell denotes mean with standard deviation in a parenthesis. The data is constructed by scraping approximately 140 bestsellers on Amazon and 40 on Walmart each week simultaneously and they are aggregated at monthly-level.

Table 2 summarizes the kitchen appliance panel across Amazon and Walmart by logistics choice. These data include key variables for the model estimation and counterfactual analyses, such as sales proxies, logistics choices across both platforms, prices, and fulfillment fees. The summary statistics show that platform-integrated logistics account for the vast majority of listings on both marketplaces: 89% on Amazon (FBA) and 79% on Walmart (WFS). Across both platforms, products using integrated logistics are systematically cheaper and lighter than those using independent logistics; on Amazon, for instance, FBA products average $70 in price and 12 pounds in shipping weight, compared to $122 and 21 pounds for independent logistics products. Conditional on using platform logistics, fulfillment fees are comparable across channels ($12.3 for FBA and $11.8 for WFS), though Walmart's unconditional average fee is lower ($9.6 and $13.1) due to product composition. Finally, platform direct retail accounts for 27% of products on Amazon and 39% on Walmart.

Numerator Consumer Panel I additionally use the Numerator consumer panel to get information about cross-platform shopping behaviors of U.S. households. Numerator collects receipts

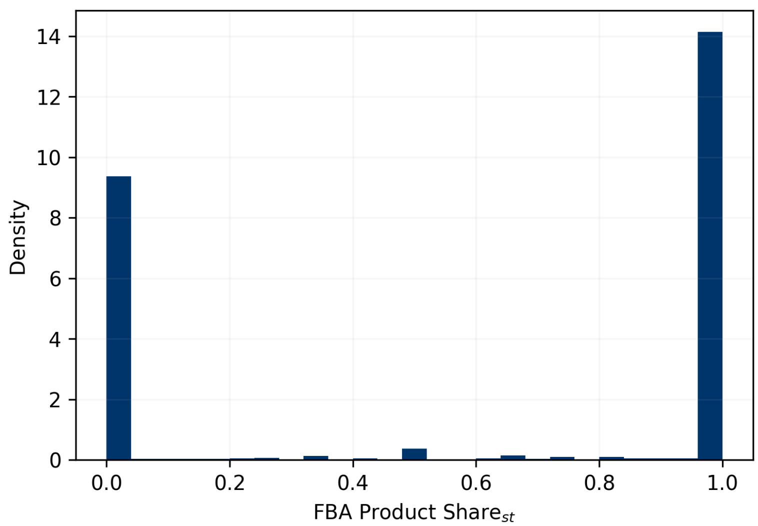
[21] JungleScout uses its own conversion formula to attain the sales estimates. Yu (2024) uses sales estimates from JungleScout and verifies them with the actual sales records of a seller. The relationship between Bizmetrica's sales estimates and bestseller ranks show a similar rank-to-sales conversion. In the appendix figure A2, I examine the validity of the sales estimates as a proxy for actual sales.

from a panel of about 200,000 U.S. households.[22] Each panelist carries a household weight that aligns the panel to Census targets and a national projection factor that scales the panel to the U.S. household population. The data contain household demographics, including income, subscription status for Amazon Prime and Walmart+ and cross-platform shopping behaviors, which serve as important factors for the demand analysis.

3.2 Descriptive Analysis

In this section, I establish stylized facts and their implications. I first examine how Amazon sellers use Amazon logistics. I then study the relationship between FBA usage and multihoming, which is motivated by the institutional feature in Section 2: integrated logistics hinder cross-platform selling.

Figure 1: Distribution of FBA Product Share



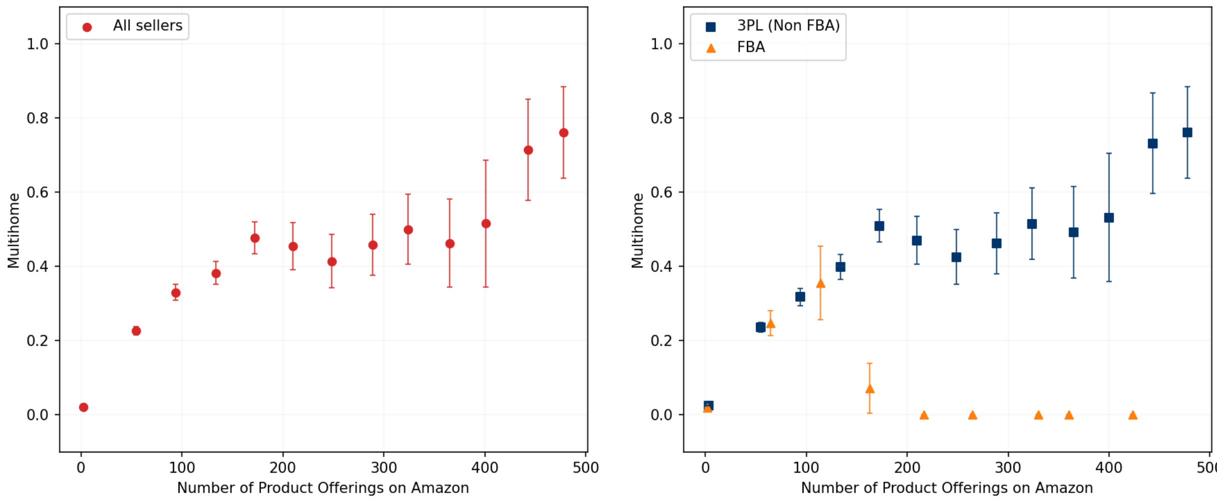
Notes. This figure shows the distribution of the share of seller s's products fulfilled by FBA in month t. The distribution exhibits a bimodal shape, massed around 0 and 1, respectively. This indicates that Amazon sellers use FBA for either all or none of their products.

The first fact is that Amazon sellers mostly use FBA for all of their products or none. Figure 1 shows the distribution of FBA product share across seller-months: it is bimodal, with mass concentrated near zero and one. This pattern follows from a simple theory that sellers prefer to using a single logistics service in order to reduce the operation costs (*FTC v. Amazon* (2023)). The bimodality also implies that the logistics decision is made at the seller level despite product-level

[22] Households join Numerator's Receipt Hog application and submit purchases by photographing paper receipts, linking online retailer accounts, and connecting email inboxes. The panel is selected from a larger pool of roughly 1.3 million annual users on two criteria: a consistent twelve-month purchase history and demographic representativeness against the U.S. Census on eight margins (gender, age, ethnicity, income, household size, presence of children, census division, and urbanicity).

fee heterogeneity.[23]

Figure 2: Multihoming and Number of Product Offerings on Amazon



(a) All Sellers

(b) By Logistics Type (FBA vs. Non-FBA)

Notes. This figure shows the relationship between multihoming and seller size. The dependent variable equals one if seller s lists at least one product on Walmart in month t. Seller size is measured by the number of product offerings on Amazon in month t. Panel (a) presents the relationship for all sellers. Panel (b) separates sellers into FBA and non-FBA types.

Second, larger sellers are more likely to multihome. I classify a seller as multihoming in a given month if it also appears on Walmart, and I measure seller size by the number of products it offers on Amazon. The binned scatter in Panel (a) of Figure 2 shows that the likelihood of appearing on Walmart rises monotonically with seller size, from near zero among the smallest sellers to roughly three-quarters among the largest. This positive relationship between size and multihoming, however, are heterogeneous by logistics methods. Splitting sellers by whether they fulfill through FBA or through a independent logistics provider, Panel (b) of Figure 2 shows that the upward-sloping size–multihoming relationship is driven by independent logistics sellers.[24].

These facts suggest that adopting FBA is negatively associated with cross-platform multihoming. This pattern is consistent with the cost-side friction: Amazon's inventory mandates require FBA sellers to commit and maintain stock within its logistics facilities, raising the cost of allocating inventory to other channels and inducing sellers to concentrate on Amazon rather than multihome. An independent logistics seller, holding channel-flexible inventory, faces no comparable constraint. However, because such adoption is correlated with many confounding factors and is likely endogenous, causality cannot be established from this descriptive exercise alone.

[23] I exploit this bimodality feature for modeling sellers' entry and logistics decisions in Section 4.

[24] To confirm the pattern, I conduct a regression of the multihoming indicator on FBA usage; Table A3 in Appendix reports the results

3.3 Regression Discontinuity Analysis

In this section, I study the impacts of FBA fees on market outcomes by using local discontinuity variations. Appendix C shows additional results and robustness checks regarding the main empirical analysis discussed below.

3.3.1 Product Categorization of FBA Fulfillment Fee Policy

In the FBA fee policy, per-unit fulfillment fee (i.e., shipping fee) is the main fee that FBA sellers pay for Amazon. The fee is calculated mainly based on two steps. First, Amazon categorizes the product into a specific product size-tier, using the product size (longest, median and shortest sides) and shipping weight. Then, Amazon applies the fee schedule corresponding to the tier on the shipping weight of the product. In general, fulfillment fees are monotonically increasing along the shipping weights.[25] The fees can significantly influence markets as they take a large portion of prices. On average, they take 26.8% of prices of FBA products on Amazon.[26]

I focus on three size-tiers, to which most of Amazon products are assigned: Small, Large, and Bulky.[27] I present the size-tier thresholds in Table 3. A product is assigned to a size tier based on its shipping weight and size — length, height, and width. If any single attribute exceeds the thresholds for a given tier, the product is assigned to the next larger tier. For example, a product weighing under one pound but exceeding 15 inches in length is classified as Large rather than Small.

Table 3: FBA Product Size-Tier

Size tier	Shipping weight (lb)	size		
		Length (in)	Height (in)	Width (in)
Small (T^S)	≤ 1	≤ 15	≤ 12	≤ 0.75
Large (T^L)	≤ 20	≤ 18	≤ 14	≤ 8
Bulky (T^B)	≤ 50	≤ 59	≤ 33	≤ 33

Notes. This table shows the definitions of FBA product size-tier. If any of criteria exceeds the thresholds, the product is assigned to be a larger size tier.

Formally, let T^L and T^B be large and bulky size-tier indicators. For tier $\in \{T^L, T^B\}$, I measure the differences from the size and shipping weight cutoffs as:

$$x_j^{\text{size,tier}} = \max\left\{l_j - c_\lambda^{\text{tier}},\ h_j - c_h^{\text{tier}},\ w_j - c_w^{\text{tier}}\right\}, \qquad x_j^{\text{shwgt,tier}} = \text{shwgt}_j - c_{\text{shwgt}}^{\text{tier}}. \tag{1}$$

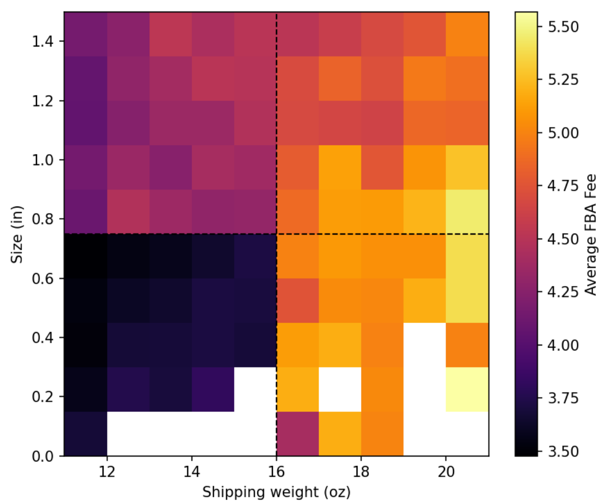
where l_j, h_j, w_j, and shwgt_j are length, height, width and shipping weight of product j and c_l^{tier}, c_h^{tier}, c_w^{tier}, $c_{\text{shwgt}}^{\text{tier}}$ are corresponding cutoff values for given tier. If one of these differences are positive,

[25] In addition to determining a product size tier, Amazon categorizes products into apparels, dangerous goods and the others. Then the same steps are applied to each category.

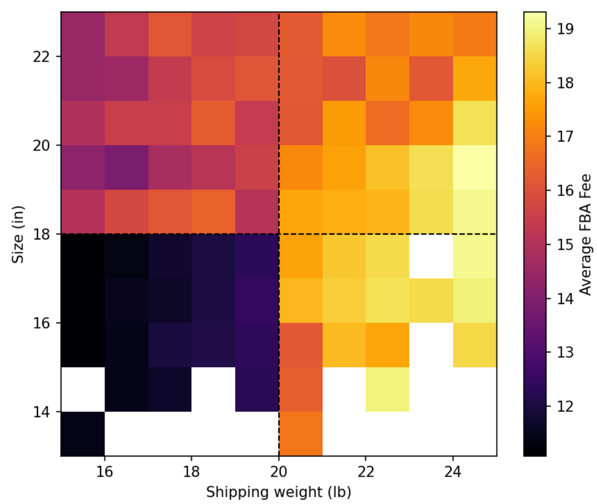
[26] The histogram of the proportions is shown in Appendix Figure A11.

[27] Their official terminologies are small standard, large standard, and small bulky.

Figure 3: Distributions of FBA Fulfillment Fees Around Product Size-Tier Cutoffs



(a) Small to Large Tier



(b) Large to Bulky Tier

Notes. This figure shows the heatmaps of FBA fulfillment fees around size-tier cutoffs defined by product size and shipping weight. Panels (a) and (b) display the distributions around the cutoffs from the small standard tier to the large standard tier and from the large standard tier to the large bulky tier, respectively. In each panel, the black dashed lines indicate cutoffs based on either product size measures ($d_j^{\text{size,tier}}$) or shipping weight measures ($d_j^{\text{shwgt,tier}}$). Each cell reports the average FBA fulfillment fee for products in the corresponding size–weight bin, averaged over time as well. The total number of products in panels (a) and (b) is 1,620 and 3,356, respectively.

the product is categorized to be larger size tier and charged higher FBA fulfillment fees.

FBA fees increase by approximately 30 to 50% upon crossing any threshold. Figure 3 displays the average FBA fulfillment fee for products binned by their distance from the cutoff in both product size and shipping weight. In both Panels (a) and (b), FBA fees jump sharply at each cutoff. Notably, products in the Small size tier are physically thin: the maximum width for this tier is 0.75 inches, so the range of relative product size to the cutoff spans from -0.75 to 0.75.

3.3.2 Regression Model

FBA's size-tier schedule generates discrete fee jumps at weight-size cutoffs as shown in Figure 3, providing variation for a regression discontinuity design. Specifically, For each combination of running-variable measure $r \in \{\text{size}, \text{shwgt}\}$ and tier $\in \{T^L, T^B\}$, I estimate the following regression model: for product j in month t,

$$y_{jt} = \beta_0 + \beta_1 \mathbf{1}(x_j \geq 0) + m(x_j) + \tau_{year(t)} + u_{jt}, \tag{2}$$

where x_j is the (normalized) running variable for product j, as introduced in (1).[28] I choose three main outcomes for y_{jt}, FBA seller ratio, prices in Amazon, and number of multihoming sellers, to examine the mechanism that FBA influences on the market. I approximate $m(\cdot)$ using a flexible local-linear specification with MSE-optimal bandwidth selection (Calonico *et al.*, 2014), allowing the bandwidth to be chosen in a data-driven way.[29] $\tau_{year(t)}$ is year fixed effects. u_{jt} is a regression error term. In specification (2), the main parameter of interest is β_1, which captures the effect of the fee increase on the outcome y_{jt}. This parameter reflects equilibrium responses of both consumers and sellers through competition in the relevant platform markets.[30] For each running-variable measure and tier, I restrict the sample to products where the other measure meets the criterion for the smaller size tier. This ensures that variation in the primary running variable alone determines tier categorization.

The interpretation of β_1 depends on whether there is sorting (manipulation) around the cutoff. In the absence of such sorting, β_1 can be interpreted as the local effect of the fee increase, holding the composition of products around the cutoff fixed. However, if sellers sort into the cheaper FBA fee regime, then β_1 absorbs also the effects of endogenous adjustment of product characteristics (packaging) and selection into treatment status. To assess the plausibility of sorting, I test for discontinuities in the density of the running variable at the cutoffs. Let $f_X(\cdot)$ denote the density of the running variable. The key hypotheses are $H_0 : \lim_{x\to 0^-} f_X(x) \leq \lim_{x\to 0^+} f_X(x)$ vs. $H_1 : \lim_{x\to 0^-} f_X(x) > \lim_{x\to 0^+} f_X(x)$ which corresponds to excess mass just below the cutoff (sorting into the cheaper regime). Figure A3 presents the density estimates. I find limited evidence of sorting around the cutoff, consistent with formal density-discontinuity tests (Cattaneo *et al.*, 2018, 2020). This suggests that FBA fees mainly affect the choice of fulfillment services, with smaller effects on product entry and packaging margins.

3.3.3 RD Estimation Results

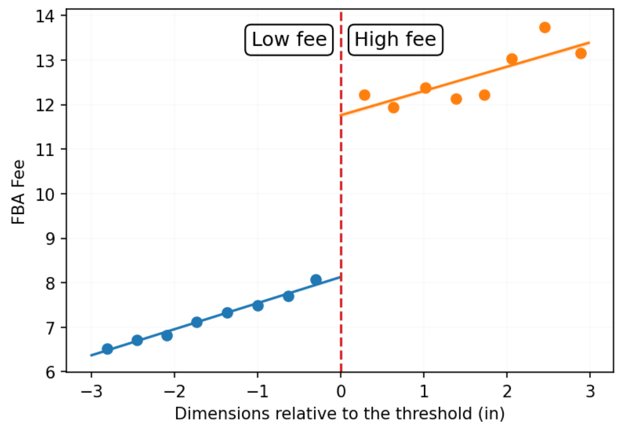
Figure 4 presents the regression discontinuity estimates. Panel (a) confirms the first stage: FBA fees jump by approximately 50% at the size-tier cutoff, from roughly \$8 to \$12. The remaining panels show how sellers and prices respond to this fee increase. Panel (b) shows that the share of third-party sellers using FBA drops sharply at the cutoff, from about 0.65 to 0.20. Panel (c) shows that prices on Amazon rise discontinuously, consistent with sellers passing FBA fee increases through to consumers. Panel (d) shows that the number of multihoming sellers increases at the cutoff, from

[28] Keepa provides length and weight not in inches and pounds but in millimeters and grams. Therefore, additional conversion of metrics is necessary to match with Amazon's product size tier criteria, which may induce rounding errors. To account for this, I exclude observations that are close to product size and shipping weight cutoffs less than 0.1 inch and pound.

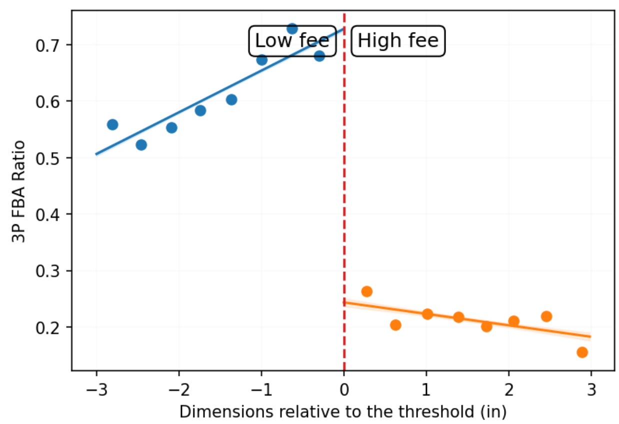
[29] It is documented that RD estimators are sensitive to global high-order polynomial approximations (Gelman and Imbens, 2019). Following their recommendations, I use low-order local-linear regressions to approximate $m(\cdot)$.

[30] Because potential outcomes would depend on the outcomes of competing products (i.e., interference), the estimand in this paper should not be interpreted as the standard average treatment effect at the cutoff targeted by textbook RD designs (e.g., Lee and Lemieux (2010)).

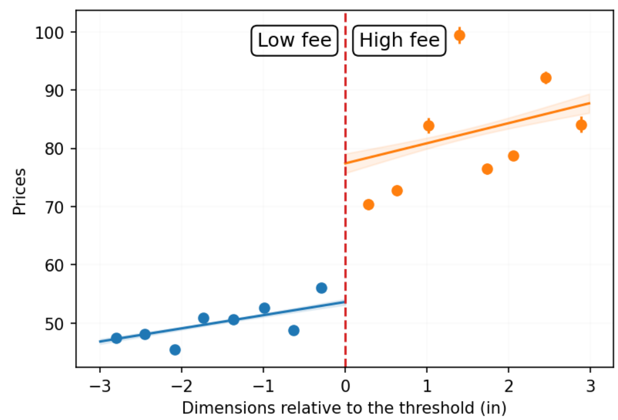
Figure 4: Regression Discontinuity Analyses



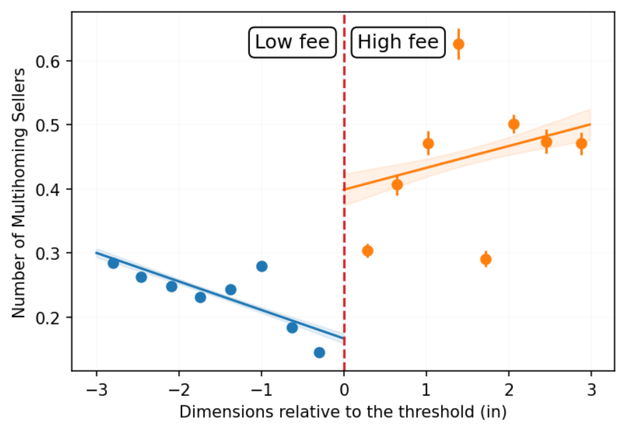
(a) FBA Fees



(b) FBA Seller Ratio



(c) Prices on Amazon



(d) Multihoming

Notes. This figure presents the regression discontinuity estimates from (2) around the large size-tier cutoff, using the product-size running variable. In each panel, the horizontal axis is the normalized distance to the cutoff: positive values correspond to products in the larger size tier, which are charged higher FBA fulfillment fees, and negative values correspond to products in the smaller tier. Dots are averages of the outcome within bins of the running variable, and the solid lines are local-linear fits estimated separately on each side of the cutoff with MSE-optimal bandwidths (Calonico *et al.*, 2014); shaded regions denote 95% confidence intervals. Panel (a) plots the FBA fulfillment fee and confirms the discontinuous fee increase at the cutoff. Panel (b) plots the share of sellers using FBA, panel (c) plots prices on Amazon, and panel (d) plots the number of multihoming sellers.

roughly 0.18 to 0.40.

These results support the causal link from using FBA to multihoming behavior and imply that FBA can substantially influence market and welfare outcomes. When FBA fees rise, sellers substitute away from FBA. Some of these sellers switch to independent logistics providers, which can serve multiple platforms from a single inventory pool. This is reflected in the simultaneous decline in FBA adoption in panel (b) and increase in multihoming in panel (d): the same cost increases that pushes sellers off FBA also loosens their tie to Amazon as a sales channel. The price increase in panel (c) confirms that FBA fees are not simply absorbed by sellers but are passed through to consumers, ultimately affecting consumer welfare.

4 Empirical Model of Vertically Integrated Platform Economy

Motivated by the evidence from the RD analysis, I develop an equilibrium model to quantify the welfare effects of vertical integration and policy interventions. On the demand side, the goal is to capture consumer preferences over product characteristics withe the focus on prices, logistics services, and platforms. This preference determines price sensitivity, utility from logistics service, and cross-platform substitution pattern that are the key primitives for counterfactual analyses. On the supply side, the model characterizes variable and fixed costs of sellers as functions of their logistics choices. This is because, given the demand function, the cost structure pins down how sellers trade off demand and cost-side (dis)advantages from using an integrated logistics that is the main margin of this research. The central challenge is to accurately recover these primitives while keeping the tractability of the model for counterfactual analyses.

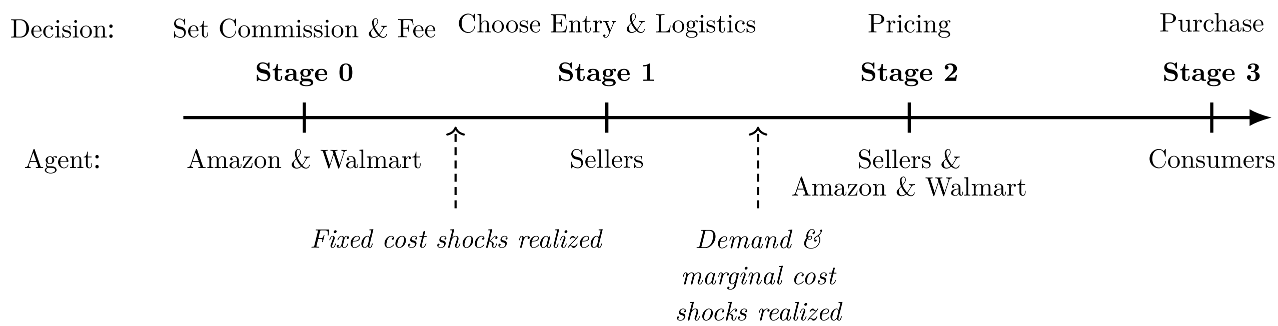
Model Overview A market is defined as a subcategory—month pair (c, t). On the demand side, consumers with heterogeneous preferences choose among differentiated products listed on Amazon and Walmart, or an outside option. On the supply side, sellers make decisions in two stages. In the first stage, sellers simultaneously choose which platforms to enter and which logistics service to use on each platform. After entry and logistics decisions are made, demand and marginal-cost shocks are realized. In the second stage, sellers observe these shocks and set prices. Commission rates and logistics fees are taken as given to consumers and sellers; they are set before sellers make any decisions. Figure 5 summarizes the timeline with the timing of realization of structural errors.

The timing assumption is based on institutional details as introduced in 2. Commission rates are stable across time on both platforms and both Amazon and Walmart announce logistics fee structures on a periodic basis. For example, Amazon updates FBA fee schedules usually on a yearly basis with prior notice. Sellers observe these schedules and make decisions on a more frequent and responsive basis. The schedule is a publicly observable menu and sellers behave accordingly. Unlike fee schedules, retail prices change much more frequently, so that a simultaneous game structure is more suitable than a sequential one when it comes to own-product retail decisions.

4.1 Consumer Demand

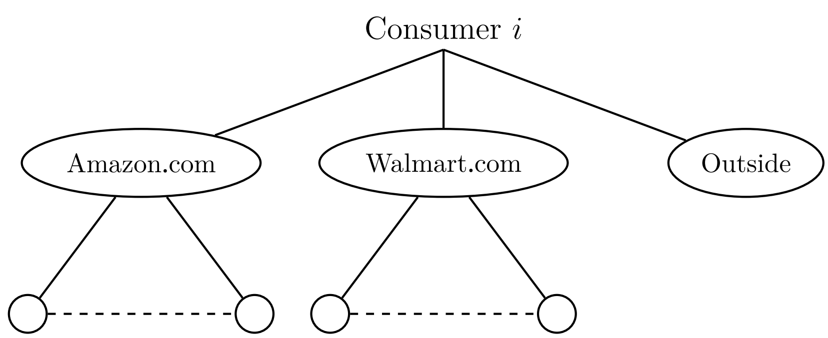
I characterize consumers by their income level, platform membership subscription, and idiosyncratic random tastes. Consumers are first divided into four income groups based on their annual income level: under 50K, 50k to 100k, 100k to 150k, and over 150k. I further represent consumers by their Amazon Prime and Walmart+ membership subscription status. Therefore, there are 16 $(= 4 \times 2 \times 2)$

Figure 5: Model Timeline



types that consumers are associated with.[31] To capture cross-platform substitution patterns, I introduce a nest structure as in McFadden (1977) in which a nest is defined as a platform.[32] Figure 6 visualizes the nest structure.

Figure 6: Nest Structure of Consumer Choice



Notes. This diagram displays the nest structure of the consumer choice model.

To accommodate the heterogeneous preferences on product and platform characteristics, I also include demographic interactions and random coefficients with taste shocks (Berry *et al.*, 1995; Petrin, 2002).

[31] I also consider the presence of nearby Walmart offline stores as an additional demographic feature of consumers. This is mainly to capture diversion to Walmart physical stores. However, almost 90% of U.S. households live within 10 miles of Walmart offline stores (Walmart, 2022), so the geographic variation of distances is not informative to identify the diversion.

[32] An alternative model of consumer choice is consumers have a specific product wish to buy and compare the same product across the two platforms. The main reason for choosing the main specification in the paper instead of this model is to capture the cross-product substitution within a platform. This is a shopping behavior supported by an experimental evidence in (Farronato *et al.*, 2026). To be specific, they show that when they randomly hide Amazon products on the search page, consumers tend to shop within Amazon, rather than visiting a competing platform.

Consumer Utility Consumer i gets indirect utility from purchasing product j on platform f in month t as:

$$\begin{aligned} U_{ijft} = \beta_i^p \log(p_{jft}) + \beta_i^{\text{FBA}} \text{FBA}_{jft} + \beta^{\text{WFS}} \text{WFS}_{jft} + \beta_i^{\text{Wmt}} \text{Wmt}_{jft} \\ + X'_{jft}\beta^x + \xi_{b(j)} + \xi_{jft} + \epsilon_{ijft} \end{aligned} \tag{3}$$

The first line captures the key variables. The coefficient β_i^p on log prices ($\log(p_{jft})$) governs price sensitivity that varies by income levels and taste shock. Specifically, the coefficient is modeled as:

$$\beta_i^p = \beta_0^p + \sum_{k \in \{1,2,3\}} \beta_k^p 1\{i \in \text{Inc}_k\} + \beta_{\text{Prime}}^p \text{Prime}_i + \beta_{\text{W}^+}^p \text{W}_i^+ + \sigma^p u_i^p \tag{4}$$

where Inc_1, Inc_2, and Inc_3 denote income groups whose annual income level is between 50k to 100k, 100k to 150k, and over 150k. Also, $\text{Prime}_i = 1\{i \text{ subscribes Amazon Prime}\}$ and $\text{W}_i^+ = 1\{i \text{ subscribes Walmart } +\}$. This specification allows for different level of price sensitivity by income level of a consumer and membership status. Additionally, u_i^p is an i.i.d. random preference shock from the standard normal distribution. This shock captures residual unobserved heterogeneity in prices that is not explained by their observed income group. σ^p is the additional parameter to be estimated, which determines how much variations in price sensitivity exist. These interactions and random terms are flexible enough to

The indicators FBA_{jft} and WFS_{jft} equal one when the product is fulfilled by the platform's integrated logistics on Amazon and Walmart, respectively. Their coefficients β_i^{FBA} and β^{WFS} contains the utility consumers derive from the associated service quality. To consider cross-platform substitution pattern by the membership status, I allow for the utility from FBA products to differ by Prime subscription as the high quality service—such as fast shipping and reliability—is exclusive for Prime subscribers. To be specific,

$$\beta_i^{\text{FBA}} = \beta_0^{\text{FBA}} + \beta_{\text{Prime}}^{\text{FBA}} \text{Prime}_i \tag{5}$$

I incorporate Walmart+ membership program in a different fashion to account for the program details. Walmart provides 2-day shipping on WFS items to *every* customer regardless of their membership status.[33] Instead, the membership is associated with other Walmart services such as grocery delivery and savings on fuel charges. As this associated perk can generate cross-platform substitution, I include the interaction between the platform dummy and Walmart+ membership as:

$$\beta_i^{\text{Wmt}} = \beta_0^{\text{Wmt}} + \beta_{\text{W}^+}^{\text{Wmt}} \text{W}_i^+ \tag{6}$$

on the dummy variable Wmt_{jft} indicates the product is listed on Walmart.com.

[33] Walmart offers free shipping on WFS items, provided consumers meet a $35 basket minimum. Walmart+ does not unlock a new tier of shipping speed for WFS items; rather, it waives the $35 minimum for the entire platform.

I control for organic search ranks in X_{jft} to separate the demand effect of fulfillment quality from algorithmic prominence that FBA products receive in search results. Specifically, I include search rank tier indicators constructed by grouping every ten position ranks.[34] The remaining observed characteristics in X_{jft} include star ratings, number of reviews, log of product shipping weight, material dummies, and whether the product is sold by the platform directly. $\xi_{b(j)}$ are brand fixed effects. ξ_{jft} is an unobserved demand shock at the product–platform–month level.

The error structure reflects the platform-level nesting in Figure 6. Consumers who have chosen to shop on Amazon substitute more readily among Amazon products than they do toward Walmart products or toward the outside option, and symmetrically for Walmart. I capture this pattern by defining a nest as a platform, so that $\mathcal{F} = \{\text{Amz}, \text{Wmt}\}$ indexes the inside nests and the outside option $j = 0$ sits in its own nest. Specifically, the error term ϵ_{ijft} can be decomposed as:

$$\epsilon_{ijft} = \bar{\epsilon}_{ift} + (1-\rho)\bar{\epsilon}_{ijft} \tag{7}$$

where $\bar{\epsilon}_{ijft}$ is an i.i.d. Type I extreme value shock and $\bar{\epsilon}_{ift}$ is the unique random variable such that the sum $\bar{\epsilon}_{ift} + (1-\rho)\bar{\epsilon}_{ijft}$ is itself Type I extreme value (Cardell, 1997). The parameter $\rho \in [0, 1)$ governs the within-platform correlation of unobserved idiosyncratic tastes: higher ρ means consumers substitute more readily within a platform than across platforms, and $\rho = 0$ collapses the model to a standard random-coefficients logit.

Market Shares Consumers choose the product that maximizes their utility among products in the choice set. Let sh_{ijft} be an consumer i's choice probability. Aggregate market shares, sh_{jft}, are derived by integrating over the joint distribution of observable demographics and the unobserved taste shocks u_i^p:

$$\text{sh}_{jft} = \sum_{\tau \in \mathcal{G}} w_{\tau t} \int \text{sh}_{ijft}(\tau, u)\, f(u)\, du, \tag{8}$$

where $\mathcal{G}$ indexes the 16 observable consumer type group (income group $\times$ Prime $\times$ Walmart+), $w_{\tau t}$ are the household weights for each type in month t, and $f(\cdot)$ is the standard normal density. Derivation of market share is provided in appendix D.1 in detail.

4.2 Seller Supply

Considering the demand, each seller s makes decisions in two stages for given month t. In the first stage, sellers simultaneously choose which platforms to enter and which logistics service to adopt, incurring fixed costs. After entry and logistics decisions are made, demand and marginal-cost shocks are realized. In the second stage, after observing these shocks, sellers then set prices. The marginal cost depends on the seller's logistics choice and economies of scale, which interact

[34] The demand estimates are robust to alternative specifications that use either a linear or a log search-rank term. The main specification is to accommodate the fact that consumer search costs can vary discretely with whether the consumer searches an additional page, a feature that a linear-in-rank specification may not capture.

because integrated logistics fragments inventory across platforms. Sellers take platform policies and product portfolios as given for every decision.

Seller Profit The variable profit from selling product j on platform f in month t is

$$\pi_{jft} = \underbrace{M_{c(j)t}\,\text{sh}_{jft}}_{\equiv Q_{jft}}\left[(1-\phi_f)\,p_{jft} - AVC_{jft}\right] \tag{9}$$

where $M_{c(j)t}$ is the market size of category $c(j)$ in month t, sh_{jft} is the market share function defined in the consumer demand model, ϕ_f is the commission rate charged by platform f on product j, and AVC_{jft} is the average variable cost. Revenue net of commission is $(1-\phi_f)\,p_{jft}$ per unit.[35]

The total profit of seller s aggregates variable profits across all products and platforms. Entering into platform $f \in \mathcal{F} = \{\text{Amz}, \text{Wmt}\}$ incurs fixed costs, so the total profit is:

$$\Pi_{st} = \sum_{f\in\mathcal{F}} \sum_{j\in\mathcal{J}_{sf}} \left(\pi_{jft} \times e_{sft} - FC_{jt}\right) \tag{10}$$

where $\mathcal{J}_{sf}$ is the set of products offered by seller s on platform f, and $e_{sft} \in \{0,1\}$ is the entry indicator. FC_{jt} is the incurred fixed cost and is a function of entry and logistics choices that are introduced in section 4.2.2 below.

4.2.1 Seller Pricing and Marginal Costs

I solve the model backward, stage-by-stage. In the second stage, sellers observe demand and marginal-cost shocks and set prices to maximize variable profit, taking entry and logistics decisions from the first stage as given. Each seller solves a Bertrand–Nash pricing problem. I use both the demand and pricing models to recover the marginal costs, which are a function of fulfillment fees, shipping weight, and the seller's effective scale in addition to other cost shifters.

Pricing In the second stage, each seller s chooses prices for its products across platforms to maximize variable profit, taking entry and logistics decisions and rival prices as given. This means that the seller solves Bertrand—Nash pricing problem as:

$$\mathbf{p}_s^* = \arg\max_{\mathbf{p}_s} \sum_{f\in\mathcal{F}} \sum_{j\in\mathcal{J}_{sf}} \pi_{jf}(\mathbf{p}_s, \mathbf{p}_{-s}), \tag{11}$$

where $\mathbf{p}_s$ is the vector of prices set by seller s and $\mathbf{p}_{-s}$ collects the prices of all other sellers.

The first-order conditions from (11) yield a system that can be inverted to recover marginal

[35] The market size is defined to be the number of households who purchased any kitchen appliance among all the subcategories, N_t^H, times Google Trend search interest of the subcategory that lies within 0 to 1, $\text{GoogleTrend}_{c(j)t}$. That is, $M_{c(j)t} = N_t^H \times \text{GoogleTrend}_{c(j)t}$. See section D.2 in Appendix for further detail.

costs. In vector form, for the products of seller s:

$$\mathbf{p}_s = \tilde{\mathbf{mc}}_s - \boldsymbol{\Omega}_s^{-1}\,\mathbf{s}_s \tag{12}$$

where $\tilde{\mathbf{mc}}_s$ is the vector of commission rate absorbed marginal costs (i.e. $\tilde{mc}_{jft} = \frac{mc_{jft}}{1-\phi_f}$) and $\boldsymbol{\Omega}_s$ is the matrix of own- and cross-price demand derivatives for seller s's products and $\mathbf{s}_s$ is the vector of market shares.[36] I recover $mc_{jft} = (1-\phi_f)\tilde{mc}_{jft}$ and parameterize independent seller's marginal costs in the next section. The marginal costs of platform's own-retail are also recovered in the same fashion while $\phi_f = 0$ holds. I do not specify the function of own-retail marginal costs and use them as they are recovered throughout the analyses.

Aside from the commission rate, this is the standard markup equation from differentiated-product oligopoly, adapted to the multi-platform setting. The key feature is that, for a multihoming seller who lists products on both Amazon and Walmart, the matrix $\boldsymbol{\Omega}_s$ captures cross-platform demand derivatives. A multihoming seller internalizes the fact that raising its price on Amazon may divert some demand to its own listing on Walmart, and vice versa. Introducing the product in a competing platform induces cannibalization, discouraging multihoming.

Marginal Cost of Independent Seller In the marginal-cost function of an independent seller, there are three main terms that determine a seller's per-unit cost in addition to standard cost shifters: the fee paid to the platform's logistics service (if used), the cost of independent logistics (if not), and economies of scale.

I specify the marginal cost of product j on platform f in month t as:

$$\begin{aligned} mc_{jft} = \; & \underbrace{\gamma^{\ell}\,\text{fee}^{\ell}_{jf}\,\ell_{jft}}_{\text{platform logistics fee}} + \underbrace{\gamma^{\text{UPS}}\,\text{fee}^{\text{UPS}}_{j}\,(1-\ell_{jft})}_{\text{independent logistics fee}} + \underbrace{\gamma^{Q}\bar{Q}_{s(j)ft}}_{\text{scale economies}} \\ & + \mathbf{W}'_{jf}\gamma^{W} + \omega_{c(j)} + \omega_t + \omega_{jft} \end{aligned} \tag{13}$$

where ℓ_{jft} is an indicator for whether the product uses the platform's integrated logistics (FBA on Amazon, WFS on Walmart), fee^{ℓ}_{jf} is the platform fulfillment fee, $\text{fee}^{\text{UPS}}_{j}$ is the posted UPS shipping rate, and $\bar{Q}_{s(j)ft}$ is the effective scale of the seller. The term $\mathbf{W}_{jf}$ is a vector of cost-shifters (material dummies, major brand indicators, third-order polynomial in shipping weights and an Amazon-market dummy), while $\omega_{c(j)}$ and ω_t are category and month fixed effects, respectively. Finally, ω_{jft} is an i.i.d. marginal cost shock.

The coefficient on the platform logistics fee is restricted to $\gamma^{\ell} = 1$. This normalization reflects that the fulfillment fee is a per-unit cost that the seller pays directly to the platform. When a seller

[36] Each element of $\boldsymbol{\Omega}_s$ is $\Omega_{jk} = \partial s_{jf}/\partial p_{kf'}$ for products $j,k \in J_s$, where products may be listed on different platforms f, f'. The matrix is non-zero off the diagonal when the same seller lists products on multiple platforms and a price change on one platform affects demand on the other.

does not use the platform's logistics ($\ell_{jft} = 0$), it ships through an independent provider. Because I do not observe exact independent logistics fees, I instead proxy for them with the posted UPS rate $\text{fee}_j^{\text{UPS}}$. UPS and FedEx are the two largest parcel carriers, and their posted schedules are nearly identical, so UPS is representative of the independent logistics option. The coefficient γ^{UPS} therefore captures the average fraction of the posted rate actually paid.[37]

Scale economies arise through volume discounts on storage, shipping, and wholesale procurement, operating through $\bar{Q}_{s(j)ft}$. When a seller uses a common independent logistics provider across platforms, it can pool inventory and aggregate volume. When a seller uses a platform's integrated logistics on any platform, inventory is fragmented and scale is limited to single-platform volume. Formally,

$$\bar{Q}_{sft} = \begin{cases} Q_{sft} & \text{if } \ell_s = 1 \\ \displaystyle\sum_{f' \in \mathcal{F}} Q_{sf't} & \text{if } \ell_s = 0, \end{cases} \tag{14}$$

where $\ell_s = \max_{f \in \mathcal{F}}\{\ell_{sf}\}$ indicates whether the seller uses integrated logistics on any platform, and $Q_{sft} = \sum_{j \in \mathcal{J}_{sf}} Q_{jft}$ is the seller's total volume on platform f. The resulting fragmentation might reduce the seller's effective scale on each platform, raising per-unit costs through the scale economy channel. Therefore, the choice of logistics creates scale spillovers; because the seller's effective scale is the function of whether to use integrated logistics or not, marginal costs across *both* platforms (mc_{sf} and $mc_{sf'}$) shift.

4.2.2 Entry and Logistics Choice with Fixed Costs

In the first stage, each independent seller s simultaneously chooses which platforms to enter and which logistics arrangement to use on each platform. Omitting the month subscript t, the seller's decision vector is:

$$\mathbf{d}_s = (e_{s\text{Amz}},\ e_{s\text{Wmt}},\ \ell_{s\text{Amz}},\ \ell_{s\text{Wmt}}) \in \mathcal{D}$$

where $e_{sf} \in \{0, 1\}$ indicates entry into platform f, $\ell_{s\text{Amz}} \equiv \text{FBA}_s \in \{0, 1\}$ indicates the use of FBA (relevant only if $e_{s\text{Amz}} = 1$), and $\ell_{s\text{Wmt}} \equiv \text{WFS}_s \in \{0, 1\}$ indicates the use of WFS (relevant only if $e_{s\text{Wmt}} = 1$). Modeling the logistics decision at the seller level rather than the product level is motivated by the bimodal pattern of FBA adoption documented in Figure 1—sellers store either all or none of their products at Amazon's facility. By omitting the infeasible case (e.g., using FBA to Amazon orders without entering into Amazon marketplace), sellers can choose among 8 decisions.

Sellers choose their decision vectors to maximize expected total profit, taking their own product

[37] This interpretation is supported by an opinion from an industry expert. Typically, sellers (or the independent logistics provider) pay a discounted rate off UPS's posted schedule, negotiated between the seller and the carrier.

portfolio and the decisions of all other sellers as given:

$$\mathbf{d}_s^*(\mathbf{d}_{-s}) = \arg\max_{\mathbf{d}_s \in \mathcal{D}} \ \mathbb{E}_{(\xi,\omega)} \left[\Pi_s(\mathbf{d}_s, \mathbf{d}_{-s})\right], \tag{15}$$

where the expectation is over the demand and marginal-cost shocks.

Fixed Cost The fixed cost of seller s introducing product j at month t according to the decision $\mathbf{d}_s$ is

$$FC_{jt}(\mathbf{d}_s) := \overline{FC}(\mathbf{d}_s) + \nu_{jt}(\mathbf{d}_s) \tag{16}$$

where $\overline{FC}$ is the mean fixed cost for decision $\mathbf{d}$, and $\nu_j(\mathbf{d})$ is a decision-specific, mean-zero stochastic fixed cost shock (i.e., $\mathbb{E}\left[\nu_j(\mathbf{d})\right] = 0$). Here, $\overline{FC}(\mathbf{d}_s)$ is the parameter of interest to be estimated. The fixed costs include both the upfront setup costs of an e-commerce business, such as initial stocking, listing, branding, and marketing, and the opportunity cost of each decision vector, which are not absorbed in the marginal costs (i.e., variable costs).

4.3 Platform Duopoly

At the beginning (Stage 0) of the game, platforms set commission rates (ϕ_f) and logistics fees (fee_{jf}) to maximize the total profit. Platforms also set retail prices of its own products, i.e., first-party retail, in the second stage, simultaneously with independent sellers.[38] The profits of platform f can be written as:

$$\begin{aligned}
\Pi_f &= \Pi_f^{1\text{P}} + \Pi_f^{\ell} + \Pi_f^{\text{Com}} \\
\Pi_f^{1\text{P}} &= \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}_{ft}^{1\text{P}}} \left(p_{jft} - mc_{jft}^{1\text{P}}\right) Q_{jft} \\
\Pi_f^{\ell} &= \sum_{s \in \mathcal{S}^{\text{Ind}}} \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}_{sft}} \left(\text{fee}_{jf}^{\ell} - mc_{jf}^{\ell}\right) \ell_{sft} e_{sft} Q_{jft} \\
\Pi_f^{\text{Com}} &= \sum_{s \in \mathcal{S}^{\text{Ind}}} \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}_{sft}} \phi_f \, p_{jft} \, e_{sft} Q_{jft}
\end{aligned} \tag{17}$$

where $\mathcal{T}$ is the set of months, $\mathcal{J}_f^{1\text{P}}$ is the set of products offered by platform f, and $mc_{jft}^{1\text{P}}$ is the marginal cost of own-product retail. In the second stage in which every structural shock is realized, platform f maximizes the total profit through retail pricing as:

$$\mathbf{p}_f^{1\text{P}*}(\mathbf{p}_{-f}) = \arg\max_{\mathbf{p}_f^{1\text{P}}} \Pi_f(\mathbf{p}_f^{1\text{P}}, \mathbf{p}_{-f}) \tag{18}$$

where $\mathbf{p}_f^{1\text{P}}$ is the vector of own-product retail prices and $\mathbf{p}_{-f}$ is the vector of prices of all the other products, including prices charged by competing platform and independent sellers on every

[38] Platforms do not participate in the first-stage entry and logistics choice. Their entry and logistics choises are fixed as observed.

platform. In the initial stage 0, platform f maximizes the expected total profit through fee charges and commission rates as:

$$\left(\mathbf{fee}_f^{\ell *}(\mathbf{fee}_{-f}^{\ell}, \phi_{-f}), \phi_f^*(\mathbf{fee}_{-f}^{\ell}, \phi_{-f})\right) = \arg \max_{(\mathbf{fee}_f^{\ell}, \phi_f)} \mathbb{E}\left[\Pi_f\left(\mathbf{fee}_f^{\ell}, \phi_f, \mathbf{fee}_{-f}^{\ell}, \phi_{-f}\right)\right] \tag{19}$$

where $\mathbf{fee}_f^{\ell}$ is the vector of every logistics fee on platform f and $-f$ denotes the rival platform. The platform takes expectation over distributions of structural shocks that include demand (ξ), marginal cost (ω) and fixed cost shocks (ν). To simplify the platform pricing model in (19), I parameterize both the fee schedule and the logistics marginal cost as proportional to the observed schedule. Let $\overline{\text{fee}}_{jf}^{\ell}$ denote the observed logistics fee of product j on platform f (the FBA schedule for Amazon and the WFS schedule for Walmart), and let

$$\text{fee}_{jf}^{\ell} = \lambda_f \, \overline{\text{fee}}_{jf}^{\ell}, \qquad mc_{jf}^{\ell} = \kappa_f^{\ell} \, \overline{\text{fee}}_{jf}^{\ell}, \tag{20}$$

where $\lambda_f > 0$ scales every product fee proportionally and $\kappa_f^{\ell} > 0$ is the platform's fulfillment cost per dollar of the baseline schedule. The observed schedule corresponds to $\lambda_f = 1$, and the platform earns the per-unit fulfillment margin $\left(\lambda_f - \kappa_f^{\ell}\right) \overline{\text{fee}}_{jf}$ on every fulfilled unit. To state the first-order conditions, I first define the platform's fulfillment revenue at the baseline schedule and its commission base as

$$R_f^{\ell} \equiv \sum_{s \in \mathcal{S}^{\text{Ind}}} \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}_{sft}} \overline{\text{fee}}_{jf} \, \ell_{sft} \, e_{sft} \, Q_{jft} \qquad R_f^{\text{Com}} \equiv \sum_{s \in \mathcal{S}^{\text{Ind}}} \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}_{sft}} p_{jft} \, e_{sft} \, Q_{jft} \tag{21}$$

Under (20), the platform profit can be written as $\Pi_f = \Pi_f^{1\text{P}} + \left(\lambda_f - \kappa_f^{\ell}\right) R_f^{\ell} + \phi_f \, R_f^{\text{Com}}$. Then, the first-order conditions of (19) are:

$$\lambda_f = \underbrace{\kappa_f^{\ell}}_{\text{logistics cost}} + \underbrace{\frac{\mathbb{E}\left[R_f^{\ell}\right]}{-\mathbb{E}\left[dR_f^{\ell}/d\lambda_f\right]}}_{\text{logistics markup (+)}} + \underbrace{\phi_f \frac{\mathbb{E}\left[dR_f^{\text{Com}}/d\lambda_f\right]}{-\mathbb{E}\left[dR_f^{\ell}/d\lambda_f\right]}}_{\text{commission-base erosion (-)}} + \underbrace{\frac{\mathbb{E}\left[d\Pi_f^{1\text{P}}/d\lambda_f\right]}{-\mathbb{E}\left[dR_f^{\ell}/d\lambda_f\right]}}_{\text{1P demand diversion (+)}} \tag{22}$$

$$\phi_f = \underbrace{\frac{\mathbb{E}\left[R_f^{\text{Com}}\right]}{-\mathbb{E}\left[dR_f^{\text{Com}}/d\phi_f\right]}}_{\text{commission markup (+)}} + \underbrace{\left(\lambda_f - \kappa_f^{\ell}\right) \frac{\mathbb{E}\left[dR_f^{\ell}/d\phi_f\right]}{-\mathbb{E}\left[dR_f^{\text{Com}}/d\phi_f\right]}}_{\text{logistics-margin erosion (-)}} + \underbrace{\frac{\mathbb{E}\left[d\Pi_f^{1\text{P}}/d\phi_f\right]}{-\mathbb{E}\left[dR_f^{\text{Com}}/d\phi_f\right]}}_{\text{1P demand diversion (+)}} \tag{23}$$

These first-order conditions decompose the observed rates into interpretable components: the fee condition splits the observed schedule into the logistics cost rate and three adjustment terms, while the commission condition consists of the three adjustment terms alone. The adjustments formalize the central tension of integrated platform pricing: market power versus commission incentives. The markup terms capture market power—incentives to increase fees and rates above the costs.

They are pinned down by the (expected) inverse of semi-elasticity of revenue bases with respect to corresponding fee and rate charges. The logistics revenue base in (21) has both logistics choice and entry margins, therefore, platforms should consider sellers' incentive to join the platform. In contrast, the commission base does not directly consider the logistics choice margin. Competition with the rival platform disciplines how sensitive sellers are to logistics fees and commission rates, as they can substitute toward the rival.

The erosion terms capture the commission incentive that disciplines this market power. The two bases are complementary: a higher logistics fee raises sellers' costs and retail prices and thus shrinks the commission base ($dR_f^{\text{Com}}/d\lambda_f < 0$), while a higher commission depresses sales and thus fulfilled volume ($dR_f^{\ell}/d\phi_f < 0$). Because the platform internalizes the complementary margin—the commission rate ϕ_f in (22) and the fulfillment margin ($\lambda_f - \kappa_f^{\ell}$) in (23)—each erosion term is negative and pulls the rate below its stand-alone level. The 1P demand-diversion terms reflect the platform's third role as a retail competitor to its own sellers. Given platforms' and independent sellers' products are substitutes, a higher fee or commission raises independent sellers' prices and diverts demand toward the platform's own listings, so both diversion terms are positive—a classic force of raising rivals' costs (Salop and Scheffman, 1983). Each observed rate therefore balances two upward forces, markup and diversion, against one downward force, erosion.

The decomposition also clarifies what vertical separation changes. If logistics is divested to an independent provider with pricing power, the provider sets λ_f without earning commissions or first-party profit, so the commission-base-erosion and diversion terms drop out of (22); the platform continues to set ϕ_f but no longer holds the fulfillment margin, so the logistics-margin-erosion term drops out of (23). The commission loses only a downward term and therefore tends to rise. The logistics fee loses one downward term (erosion) and one upward term (diversion), so its direction is theoretically ambiguous.

4.4 Closing the Model

Market Equilibrium The equilibrium concept is a subgame perfect Nash equilibrium (SPNE) which consists of a Nash equilibrium in every stage. No platform and seller can increase (expected) profit by unilaterally deviating from their strategy. I assume the existence of a pure-strategy SPNE, yet do not assume the uniqueness of it.

Discussions Several limitations are worth noting. First, independent logistics providers do not participate in pricing competition, which may restrict their responses to counterfactual interventions. An alternative would treat them as a single strategic player in the pricing game, but I exclude them because of what data suggest. An analysis of fee-schedule dynamics between Amazon and other logistics providers (UPS and FedEx) shows that these providers respond little to Amazon's fee changes, suggesting they do not engage in Bertrand-style competition. This result is, however, insufficient to confirm the modeling decision, since the providers offer negotiated discounts off the posted schedules, and these discounts—rather than the posted rates—may be where competitive responses occur. To address this concern, I fix the UPS shipping rate in the counterfactual but allow γ^{UPS} to be chosen by the representative independent logistics provider, who participates in the stage-0 game, as a robustness analysis.

In addition, the model restricts competition to the online channel, omitting Walmart's extensive brick-and-mortar stores. It also does not capture other retail channels available to independent sellers beyond the Amazon and Walmart platforms, such as Shopify stores. Although I do not explicitly model these channels, I show in Appendix A.3 that substitution toward them is absorbed into the marginal cost recovered from retail pricing. Therefore, counterfactuals results can be interpreted as the changes while these incentives related to outside channels being fixed.

Lastly, the model abstracts from the platforms' intertemporal, forward-looking strategies, which matter for analyzing the dynamic equilibrium effects of logistics integration. The model does not exclude such incentives entirely, since the cost rates (c_f^ℓ) can absorb investment incentives.[39] What the static formulation cannot capture is how these incentives evolve over time, which remains a limitation. I instead regard the static equilibrium as the long-run equilibrium state of the marketplace. This focus remains adequate for the research questions of this paper, and incorporating the platforms' dynamic incentives is an important extension for future research.

5 Identification and Estimation

5.1 Consumer Demand

I identify the demand parameters by using a combination of aggregate and micro-level moment conditions. First, I use the aggregate-level moment condition as:

$$\mathbb{E}\left[\xi_{jft} \mid \mathbf{Z}^{\text{D}}_{jft}\right] = 0 \tag{24}$$

where ξ_{jft} is the unobserved demand shock in (3) and $\mathbf{Z}^{\text{D}}_{jft}$ are the demand-side instruments.

To address the endogeneity of prices, I use $\log(\text{fee}_{jf})$ as a cost shifter instrument.[40] Two arguments support the validity of this instrument. First, the instrument satisfies the exclusion restriction and is relevant by construction: the fee is excluded from consumer utility but enters the seller's marginal cost and therefore shifts equilibrium prices. Also, the institutional details of platform fee-setting corroborate exogeneity. Platforms announce their fee schedules generally at annual intervals and apply them uniformly across the marketplace. Therefore, it is unlikely that an idiosyncratic, unobserved demand shock is correlated with this predetermined fee structure, particularly con-

[39] For instance, the cost rates include the Pareto weights that platforms allocate to consumer and producer surpluses, which are explicitly modeled in Gutierrez (2022); Yu (2024).

[40] I take log to match the log price variable in the consumer demand model and to improve the first-stage fit.

ditional on a rich set of observed product characteristics. Non-price product characteristics are assumed to be exogenous and therefore instrument for themselves. I use additional instruments to identify the nesting parameter (ρ). I use the number of products in the choice set in each market to identify the nesting parameter. This gives variations in within-nest shares and is exogenous under the timing assumption.

I build micro moments to identify demographic interaction terms ($\beta_1^p, \beta_2^p, \beta_3^p, \beta_{\text{Prime}}^p, \beta_{\text{W+}}^p, \beta_{\text{Prime}}^{\text{FBA}}, \beta_{\text{W+}}^{\text{Wmt}}$) and standard deviation on price coefficients (σ^p). I compute average log of prices by income groups and membership subsriptions for pinning down interaction terms ($\beta_1^p, \beta_2^p, \beta_3^p, \beta_{\text{Prime}}^p, \beta_{\text{W+}}^p$). In addition, I calculate Amazon's inside share by Prime and Walmart+ subscription status. These moments convey information about how strongly subscription status tilts a consumer toward or away from Amazon, thereby identifying ($\beta^{\text{Prime}}, \beta^{\text{W+}}$). Lastly, I compute the second moment of log prices, which, together with the income-group averages of log prices, pins down the standard deviation of the price coefficient (σ^p). Additional details of moment construction are provided in the appendix section D.3.

I estimate the demand parameters by minimizing the GMM objective function that stacks moment conditions described above. I implement a two-step procedure to improve efficiency: I first estimate the demand parameters by using the introduced aggregate and micro moments and then use the estimates to approximate the optimal micro moments in the spirit of Chamberlain (1987).[41] Additional details of demand estimation are discussed in the appendix section D.

5.2 Marginal Costs

The key condition to identify the cost parameters in (13) is

$$\mathbb{E}\left[\omega_{jft} \mid \mathbf{Z}_{jft}^{\text{MC}}\right] = 0 \tag{25}$$

where $\mathbf{Z}_{jft}^{\text{MC}}$ is a vector of the instrumental variables.

The endogenous variable in (13) is the effective scale ($\bar{Q}$). As instruments, I consider demand shifters that are excluded from the marginal cost function (Berry and Haile, 2014), alongside the Google Trends search popularity measure. These excluded demand shifters, however, include the number of reviews and star ratings, which may be correlated with unobserved cost shocks. For instance, a negative realization of the cost shock lowers marginal cost, which raises sales and hence the number of reviews. To address this potential endogeneity issue, I use leave-one-out instruments that average each demand shifter across the other products sold by the same seller, and separately across products sold by rival sellers.[42] Instrumenting for the effective scale also mitigates the bias from the rank-to-sales conversion measurement error. This is because these instruments are

[41] I follow the estimation routines in Conlon and Gortmaker (2025)

[42] This remains valid under the weaker assumption that ω_{jft} and $x_{j'ft}$ are uncorrelated for $j' \in \mathcal{J}_{sft} \setminus \{j\}$ or $j' \in \mathcal{J}_{s'ft}$ where $s' \neq s$, and $x \in \{\text{Star Rating}, \text{Reviews}\}$.

correlated with the true sales quantity but orthogonal to the conversion error. I estimate the marginal cost function using two-stage least squares (2SLS).

5.3 Fixed Costs

I use the revealed preference rationale to identify the fixed costs in (16). In addition, I restrict the support of differences in fixed costs to account for selection bias, following Eizenberg (2014). I introduce the identification with more detail in section G.1.

Suppose a seller s chooses $\mathbf{d}_s^* \in \mathcal{D}$ as an optimal decision as in (15). Holding others' decision fixed as $\mathbf{d}_{-s}$, the revealed preference rationale with the decision rule in (15) and Nash equilibrium condition imply that for any deviation $\mathbf{d}_s' \neq \mathbf{d}_s^*$,

$$\mathbb{E}_{(\xi,\omega)}\left[\Pi_s(\mathbf{d}_s^*, \mathbf{d}_{-s})\right] \geq \mathbb{E}_{(\xi,\omega)}\left[\Pi_s(\mathbf{d}_s', \mathbf{d}_{-s})\right] \tag{26}$$

where $\mathbb{E}_{(\xi,\omega)}$ means the expectation is taken with respect to the distribution of (ξ, ω). We can rearrange these inequalities to denote the difference between the expected variable profits from the observed optimal choice $\mathbf{d}_s^*$ and any deviation $\mathbf{d}_s'$ is larger than incurred fixed cost differences of them.

These inequalities are informative as an upper and lower bound of the differences in fixed costs, yet the *selection bias* hinders us from directly using the above inequality conditions. To circumvent this selection issue, I follow the approach by Eizenberg (2014) and assume that the support of differences in fixed costs (ΔFC_s) fall within the range of the supremum and infimum of expected variable profit differences ($\bar{\pi}_s$):

$$\Delta FC_s(\mathbf{d}, \mathbf{d}') \subset \left[\inf_s \Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}'), \sup_s \Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}')\right] \text{ for any } s \in \mathcal{S} \tag{27}$$

This support restriction allows me to attain the lower and upper bounds for every decision, so I can take the *unconditional* expectation, resolving the selection bias.

The support restriction is corroborated by the highly skewed sales distributions on e-commerce platforms, often resembling a Pareto distribution (Chevalier and Goolsbee, 2003; Brynjolfsson *et al.*, 2003, 2025). This means that a small number of best-selling products account for the vast majority of sales, causing expected variable profits to vary widely across products and sellers. In addition, standardized practices, such as wholesaling, warehousing, and fulfillment, and the consequently stable cost structures of e-commerce operations further support the validity of this assumption. Stacking the moment inequalities, I estimate the set by the linear-programming method. Estimation details are in Appendix G.1.1.

6 Estimation Results

6.1 Demand Estimation Results

Table 4 reports the parameter estimates from the main demand specification, organized around the three mechanisms the model is designed to capture: cross-platform substitution, heterogeneity in price sensitivity, and valuation of logistics quality.

Table 4: Demand Estimates

		Interactions with Demographics					
Variable	Mean (1)	50–100k (2)	100–150k (3)	150k+ (4)	Prime (5)	Walmart+ (6)	Std. (σ) / Corr. (ρ) (7)
log of Prices	-3.790^{***}	0.020	0.043^{***}	0.057^{***}	0.354^{***}	0.033^{**}	0.000
	(0.367)	(0.014)	(0.015)	(0.015)	(0.039)	(0.014)	(0.005)
FBA	-0.873^{***}				1.310^{***}		
	(0.237)				(0.191)		
WFS	-0.183						
	(0.180)						
Walmart Platform	-1.300^{***}					2.070^{***}	
	(0.242)					(0.099)	
Star Ratings	0.141^{*}						
	(0.086)						
Reviews (in 1K)	0.024^{***}						
	(0.003)						
log of Shipping Weight	1.840^{***}						
	(0.201)						
1P Retailer	-0.177						
	(0.119)						
Stainless steel	0.276^{***}						
	(0.071)						
Aluminum	-0.226^{**}						
	(0.100)						
Plastic	-0.050						
	(0.072)						
Platform Nests							0.190^{***}
							(0.066)
Brand Fixed Effects				Yes			
Search Rank Tiers				Yes			
GMM objective				52.17			
Number of Observations				5,585			
Number of Markets				39			
Micro-moment Observations				41,165			
Mean Own Price Elasticity				-4.2			

Notes. This table reports parameter estimates from the demand model. Column (1) presents the mean coefficients; columns (2)–(6) present interactions of product characteristics with household demographics, and column (7) reports the standard deviation σ of the random coefficients on log price and the nesting parameter ρ for the Amazon/Walmart nest structure. Income interactions are indicators for the household income bins 50–100k, 100–150k, and 150k+, with "below 50k" as the omitted category. Prime and Walmart+ denote subscription status. Robust standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Consumers exhibit a baseline preference for Amazon: the mean coefficient on the Walmart-platform indicator is -1.300 and significant. The Walmart+ interaction of 2.070, however, more than offsets this baseline, so Walmart+ subscribers are substantially more likely to purchase on Walmart. Beyond subscriptions, the nesting parameter $\rho = 0.190$ (significant at the 1% level) indicates residual within-platform correlation in unobserved tastes.[43]

Income-based heterogeneity in price sensitivity is statistically detectable but economically modest: relative to the mean log-price coefficient of -3.790, the income-bin interactions range from 0.020 to 0.057. Prime subscribers are notably less price sensitive, with an interaction of 0.354;[44] the Walmart+ interaction is substantially smaller.[45] The standard deviation of the random coefficient on log price is close to zero, indicating little residual unobserved heterogeneity. The implied mean own-price elasticity of -4.2 is consistent with the literature (Farronato *et al.*, 2026; Yu, 2024); Figure A7 shows the full distribution.

Logistics quality is highly valued, but only through Prime. The mean FBA coefficient of -0.873 combines with the Prime–FBA interaction of 1.310 to give Prime subscribers a net utility weight of 0.437 on FBA fulfillment, while non-Prime consumers retain the negative mean coefficient. Evaluated at the median income bin of a Prime subscriber and an average price of $74, this implies a willingness to pay of approximately $9.4 per delivery, equivalent to a 12% price discount. The WFS coefficient is statistically insignificant, though non-Prime consumers value WFS above FBA, consistent with Walmart offering two-day WFS shipping on orders over $35 regardless of subscription status while non-Prime FBA shipping takes 5–8 days. Remaining characteristics carry the expected signs.

6.2 Marginal Cost Estimation Results

Table 5 reports estimates of the marginal cost function in equation (13). The coefficient on $\text{fee}^{\text{UPS}} \times (1-\ell_{sf})$, which captures the fraction of the posted UPS rate that independent sellers actually pay, is estimated between 0.598 and 0.609 across every specification and statistically significant at 1% level. The estimates imply that sellers shipping through an independent provider pay roughly 60% of the posted UPS Ground schedule—an average negotiated discount of about 40%. This magnitude is consistent with an industry expert saying sellers negotiate substantial discounts off carriers' posted rate schedules.

The scale economy parameter γ^Q is negative and statistically significant across almost every specification, indicating that sellers with larger effective volumes benefit from lower marginal costs. In the baseline linear specification of equation (13), reported in columns (2), (4), (6), and (8), each additional 1,000 units of effective monthly scale lowers a seller's marginal cost by roughly $0.06 to $0.32. The main specification, which utilizes the leave-one-out instruments, is reported in column (8) and carried into the counterfactual analysis; its estimate of -0.144 implies a reduction of about

[43]This may absorb search costs that are higher across platforms than within them.
[44]This estimate is qualitatively similar to the interaction term in Farronato *et al.* (2026).
[45]These estimates may absorb subscription-specific savings.

Table 5: Marginal Cost Function Estimates

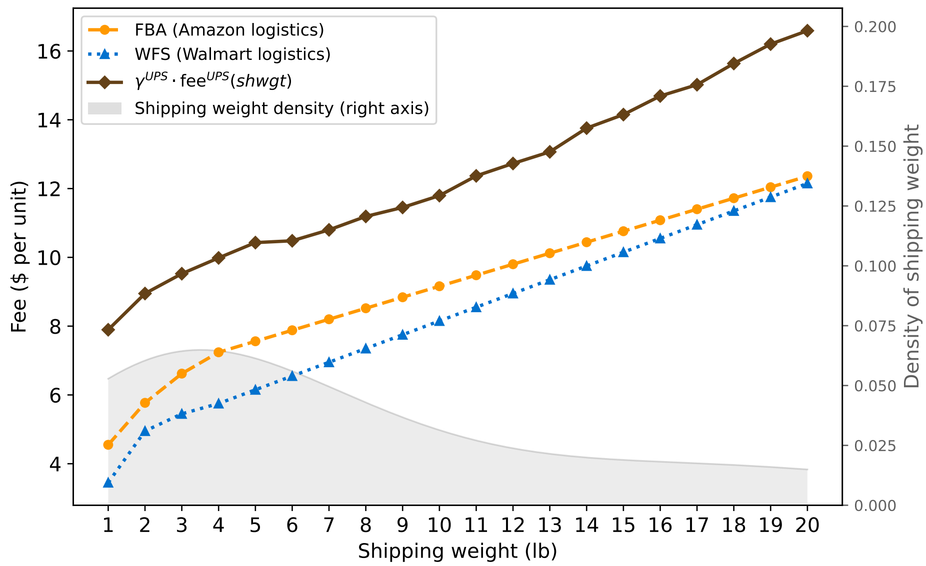
Variables	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV	(7) IV	(8) IV
$\text{fee}^{\ell} \times \ell_{sf}$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
$\text{fee}^{\text{UPS}} \times (1-\ell_{sf})$	0.601***	0.604***	0.603***	0.607***	0.601***	0.609***	0.598***	0.607***
	(0.093)	(0.093)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)
Scale Economy ($\log \bar{Q}$)	−0.597*		−1.044***		−1.811**		−2.764***	
	(0.320)		(0.325)		(0.775)		(0.615)	
Scale Economy ($\bar{Q}$)		−0.063***		−0.118***		−0.317***		−0.144***
		(0.022)		(0.026)		(0.093)		(0.047)
shwgt	3.951***	3.963***	4.242***	4.224***	4.246***	4.205***	4.252***	4.222***
	(0.227)	(0.226)	(0.260)	(0.260)	(0.259)	(0.259)	(0.259)	(0.259)
shwgt^2	−0.047***	−0.048***	−0.046***	−0.046***	−0.046***	−0.046***	−0.047***	−0.046***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
shwgt^3	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stainless Steel	6.970***	7.051***	5.129***	5.218***	5.119***	5.347***	5.108***	5.235***
	(1.157)	(1.152)	(1.360)	(1.365)	(1.353)	(1.368)	(1.354)	(1.361)
Aluminum	−3.491**	−3.269**	−0.328	−0.288	−0.394	−0.373	−0.477	−0.299
	(1.388)	(1.349)	(1.567)	(1.565)	(1.555)	(1.564)	(1.568)	(1.561)
Plastic	3.826***	3.796***	1.244	1.228	1.236	1.182	1.225	1.222
	(1.230)	(1.234)	(1.169)	(1.172)	(1.164)	(1.171)	(1.165)	(1.168)
Major Brand	9.286***	8.932***	8.730***	8.266***	9.388***	8.996***	10.205***	8.362***
	(1.946)	(1.884)	(1.913)	(1.898)	(2.176)	(2.009)	(1.976)	(1.894)
Category FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
IV	No	No	No	No	Own	Own	Rival	Rival
Observations	4,092	4,092	4,092	4,092	4,092	4,092	4,092	4,092
R^2	0.569	0.569	0.590	0.590	0.590	0.588	0.587	0.590
Weak IV F-stats					49.4	22.6	94.5	50.6

Notes. Columns (1)–(4) are OLS; columns (5)–(8) are IV with the (log or level) quantity treated as endogenous. Columns (5) and (6) use own-product demand shifters (ratings, reviews, and search rank) together with the category-level Google Trends index. Columns (7) and (8) use instruments that exclude own product characteristics: the leave-one-out sums of within-firm and competing-firm ratings and reviews, the number of first-party retail products, and the Google Trends index. The coefficient on $\text{fee}^{\ell} \times \ell_{sf}$ is constrained to one. The independent logistics fee fee^{UPS} is the posted 2025 UPS Ground rate (zone average) at the product's shipping weight. The unit of scale economy is 1,000 units. Heteroskedasticity-robust standard errors in parentheses. The reported weak-IV F is the rank-based Wald F-statistic of Kleibergen and Paap (2006). ***, **, and * indicate the coefficient estimate is statistically significant at 1, 5, and 10% level, respectively.

$0.14 per 1,000 units. The logarithmic alternative delivers the same qualitative message. The weak IV F-statistics indicate that the instruments are relevant in every IV specification.

Figure 7 translates the estimates into a direct comparison among the logistics options. The platforms' integrated fulfillment fees lie below the estimated per-unit cost of independent logistics at every shipping weight. This is evidence that platforms price their integrated logistics low relative to the market alternative, indicating that the intermediary's incentive to keep logistics fees low is active. Low fees alone, however, do not guarantee that the integrated service is more cost-effective than the independent service, because of economies of scale: by shipping through a common independent provider, sellers can pool inventory across platforms, raising their effective scale ($\bar{Q}$)

Figure 7: Logistics Fee Comparison



Notes. This figure compares the platforms' integrated fulfillment fee schedules with the estimated per-unit cost of independent logistics across shipping weights. FBA and WFS are the platforms' 2025 fulfillment fee schedules, shown for the large-standard size tier, to which most products in the sample are assigned. The brown line is the estimated per-unit fee of independent logistics, $\hat{\gamma}^{\text{UPS}}\text{fee}^{\text{UPS}}$, evaluated at the main-specification estimate $\hat{\gamma}^{\text{UPS}} = 0.607$ from Table 5. fee^{UPS} is the posted 2025 UPS Ground rate. The shaded area shows the kernel density of shipping weight in the estimation sample (right axis).

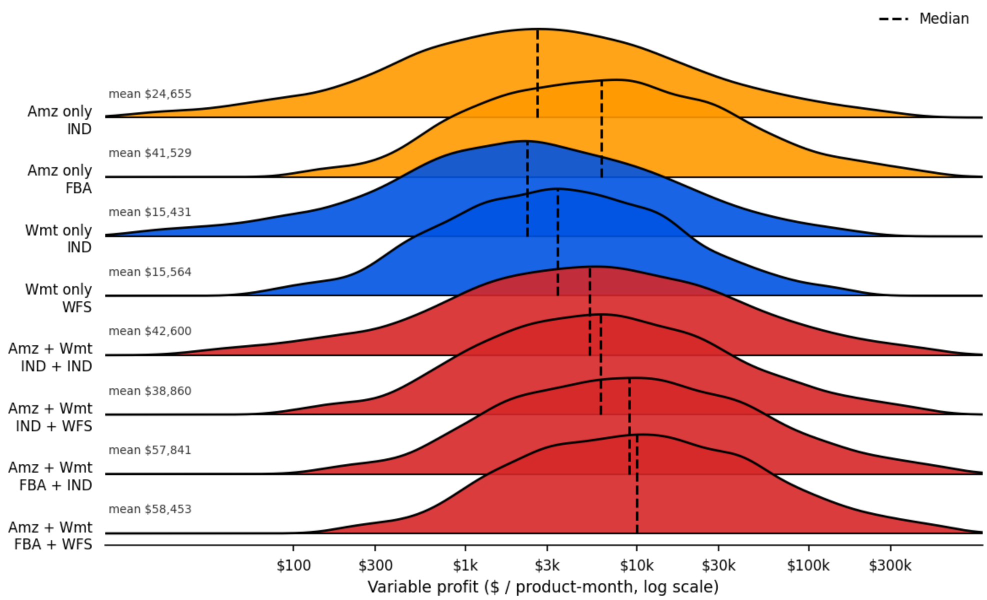
and lowering variable costs.

6.3 Estimated Variable Profits by Entry and Logistics Decisions

Using the demand and marginal cost estimates, I quantify the trade-off that sellers face in their entry and logistics choices. Specifically, I simulate each seller's variable profits under each $\mathbf{d} \in \mathcal{D}$ while holding the other sellers' decisions fixed; these profits are crucial inputs for estimating the fixed costs, because sellers directly compare the variable profit differences in order to choose optimal $\mathbf{d}$ as described in (15). The simulation details are explained in Appednix F

Figure 8 plots the distributions of simulated expected variable profit per product-month under each entry and logistics decision. There are some notable features. First, Amazon FBA increases profits, mainly through demand-side advantages. Second, using WFS and using the independent logistics on Walmart lead to similar variable profits. Third, multihoming increases variable profits, with gains from the scale economies generated by inventory pooling. Notably, multihoming with the independent logistics on both platforms yields more profit than the naive sum of the Amazon-Ind and Walmart-Ind single-homing profits, which indicates the scale benefits. Among the multihoming decisions, the (Amazon-Ind, Walmart-WFS) and (Amazon-FBA, Walmart-WFS) choices yield the smallest and largest profits, respectively, in terms of both mean and median.

Figure 8: Simulated Variable Profits by Entry and Logistics Decisions



Notes. This figure shows the estimated expected variable profits by entry and logistics decisions. Each ridge is a kernel density estimate of the distribution of simulated expected variable profit across product-months under one $\mathbf{d} \in \mathcal{D}$. The unit of observation is a product–month; variable profit is summed over the product's active platform listings. The horizontal axis is on a log scale (USD per product-month); each density is estimated on log variable profit trimmed to its 1st–99th%iles. Dashed lines mark the median and "mean" reports the full-sample mean. Orange, blue and red denote Amazon-only, Walmart-only and multihoming entry decisions, respectively. IND denotes independent logistics service.

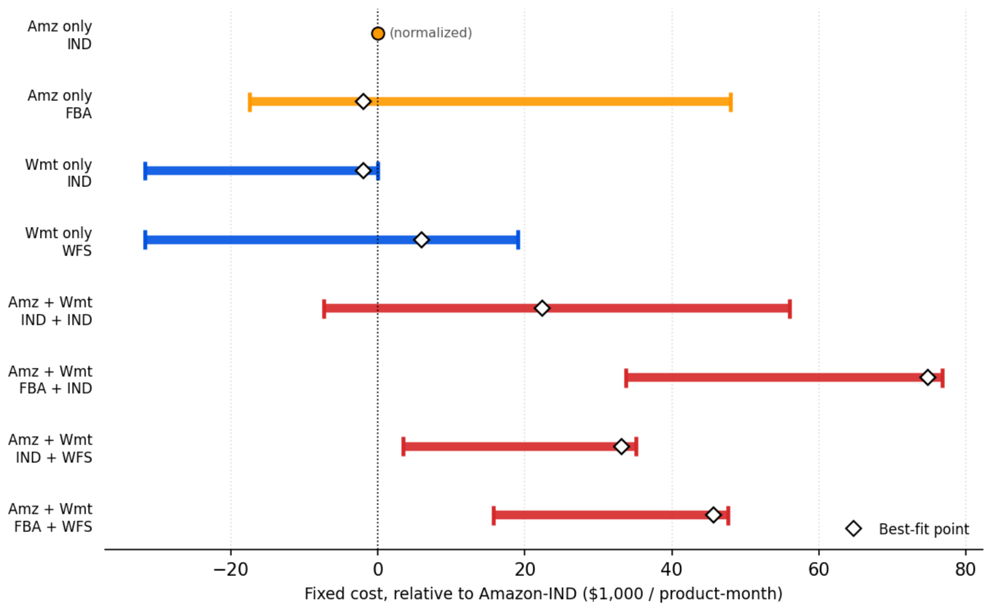
6.4 Fixed Costs Estimation Results

Figure 9 reports the fixed-cost estimates of each entry and logistics decision. All estimates are reported relative to the Amazon–independent-logistics decision, $FC(1, 0, 0, 0) \equiv 0$. The figure shows the identified-set bounds for each decision along with the best-fitting point of the identified set.[46].

There are several features worth noting. First, three of the four multihoming sets lie strictly above zero. The only multihoming decision whose identified set contains zero is the one with independent logistics on both platforms—the only configuration whose fixed cost can be comparable to those of single-homing. Second, among the multihoming decisions, the fixed cost is lowest under independent logistics on both platforms and highest when FBA is combined with independent logistics on Walmart, consistent with the data that the majority (56%) of observed multihomers operating independent logistics on both platforms. That adding WFS lowers the multihoming cost conditional on FBA suggests the two integrated services partially complementary in resolving the inventory fragmentation that FBA creates.

[46]This is the point that best predicts the observed distribution of seller choices while setting the unobserved fixed cost shocks to be zero as in Eizenberg (2014). Together with the simulated expected variable profits and decision rule (26), the best-fit point predicts 66% of observed decisions.

Figure 9: Fixed Cost Estimates by Entry and Logistics Decision



Notes. This figure shows fixed cost estimates of each decision, $\overline{FC}(\mathbf{d})$. IND denotes independent logistics. The fixed cost of Amazon-IND decision is normalized to be zero. Horizontal bars are the identified sets; diamonds mark the best-fitting point of the identified set, i.e., the point that best fits the observed distribution of seller choices when the unobserved fixed cost shocks are imputed to be zero. Orange, blue, and red denote Amazon-only, Walmart-only, and multihoming entry decisions, respectively. The number of sellers is 1 Exact values are reported in Appendix Table A5; details of the estimation and inference are in Appendix Section G.1.1.

6.5 Decomposing the Platform Pricing

The full demand and cost estimates tell us how sensitive consumers and sellers are to prices, fees and commission rates, which further informs the platforms' pricing incentives. In this section, I estimate and decompose factors of platform's pricing that internalize cross-chain spillovers where the platforms operate. This decomposition exercise directly answers the research questions about measuring the market power and commission incentive to curb that power.

I evaluate each term in the first-order conditions (22)–(23) and estimate κ_f^ℓ from the observed data.[47] I obtain the derivatives with respect to each platform's logistics fee and commission rate by taking a central-difference, simulating entry-logistics decisions, and solving the estimated second-stage price equilibrium. Given these derivatives, I solve for the unique κ_f^ℓ that rationalizes the observed schedule ($\lambda_f = 1$). This simultaneously pins down the 1P retail margins through the platforms' own retail pricing conditions.

Table 6 shows the decomposition results. I discuss the results mainly based on the best-fit point, but the implications are qualitatively consistent with more conservative partially identified results.

[47] The commission condition is evaluated at the observed $\phi_f = 0.15$, so there can be a gap between the model-implied $\hat{\phi}_f$ and observed ϕ_f.

Table 6: Decomposition of the Platforms' Fee and Commission Pricing

	Amazon	Walmart
Panel A: *fee FOC* (22)		
Logistics cost rate κ_f	0.543	0.895
	[0.377, 1.374]	[0.367, 1.752]
Logistics markup	0.636	0.431
	[0.138, 0.784]	[0.070, 0.983]
Commission-base erosion	-0.355	-0.412
	[-0.693, -0.212]	[-0.839, 0.010]
1P demand diversion	0.176	0.086
	[0.039, 0.217]	[0.014, 0.193]
Panel B: *commission FOC* (23)		
Commission markup	0.322	0.253
	[0.058, 0.381]	[0.021, 0.356]
Logistics-margin erosion	-0.130	-0.022
	[-0.142, 0.070]	[-0.058, 0.126]
1P demand diversion	0.036	0.017
	[0.007, 0.043]	[0.001, 0.024]

Notes. This table shows the estimates of each term in the first-order conditions of the platform pricing model in (19). All terms incorporate the sellers' price responses and their entry and logistics bundle re-optimization. Fixed costs are held at the best-fit point of the nonparametric mean moment-inequality estimates. Brackets report the range of each term across 50 fixed-cost vectors sampled uniformly from the joint identified set. κ_f solves the fee condition exactly at the observed $\lambda_f = 1$.

In the fee condition, the logistics markup is 0.64 on Amazon and 0.43 on Walmart: the platforms can exert significant market power through the logistics chain. The implied logistics cost rate is $\kappa_f^\ell = 0.54$ on Amazon and 0.89 on Walmart, so the per-unit logistics margin $1 - \kappa_f^\ell$ is 0.46 and 0.11: Amazon earns a sizable margin on each fulfilled unit while Walmart prices its logistics service close to cost.

The logistics markup is largely offset by commission-base erosion (-0.35 on Amazon, -0.41 on Walmart—about half the markup on Amazon and nearly the full markup on Walmart). As an integrated platform internalizes that a higher logistics fee drives sellers off the marketplace and shrinks the commission base, the platform faces downward pressure on the logistics fee. This suggests that vertically separating the logistics operator can reduce consumer and independent sellers' welfare as the independent logistics operator would not internalize any of this erosion and therefore have incentives to raise fees.

The commission rate is mainly determined by the commission markup (0.32 on Amazon and 0.25 on Walmart), with smaller contributions from the logistics-margin and 1P channels. The 1P demand-diversion terms are small relative to the other components (0.18 and 0.09 in the fee condition, 0.04 and 0.02 in the commission condition). These numbers imply that the platforms' incentive to raise costs of independent sellers in order to steer demand toward their own 1P products is relatively weak on both Amazon and Walmart. The numbers, however, are strictly above zero, which means that there still exist anti-competitive incentives and regulators should be concerned about.

7 Counterfactuals

I use the estimated demand and cost parameters to conduct counterfactual analyses. The main analysis is vertical separation of Amazon logistics, which serves as a benchmark for measuring the net welfare effects of Amazon's logistics integration. I then conduct two additional analyses: Amazon monopoly counterfactuals and interoperable Amazon logistics. The former quantifies the competitive pressure from Walmart in disciplining Amazon's pricing incentives under logistics integration. The latter measures the impact of making platform's service be available for the competing platform with the same quality and fee charges on welfare and market outcomes. This simulation analysis provides empirical evidence for many regulatory discussions on digital platform competition which revolve around enforcement of interoperability (Bourreau and Krämer, 2023; Colangelo and Martinez, 2025; Crawford *et al.*, 2023).

To evaluate the welfare outcomes, I define consumer surplus (CS) as (Small and Rosen, 1981; Petrin, 2002):

$$\text{CS} = \sum_{ct} \left[M_{ct} \sum_{i \in I_{ct}} w_{ict} \frac{\bar{p}_{ct}}{|\beta_i^p|} \log \left(1 + \sum_{f \in \mathcal{F}} \exp V_{ifct} \right) \right], \quad V_{ifct} = (1-\rho) \log \sum_{j \in J_f} \exp \left(\frac{V_{ijct}}{1-\rho} \right) \tag{28}$$

in which w_{ict} are the weights of the consumers, $V_{ijct} := \beta_i^p \log(p_{jft}) + \beta_i^{\text{FBA}} \text{FBA}_{jft} + \beta^{\text{WFS}} \text{WFS}_{jft} + \beta_i^{\text{Wmt}} \text{Wmt}_{jft} + X'_{jft} \beta^x + \xi_{b(j)} + \xi_{jft}$ in (3), and V_{ifct} is the inclusive value of platform-nest f with nesting parameter ρ. To convert consumer surplus into the money metric, I use the observed share-weighted market price $\bar{p}_{ct}$, which is held fixed across scenarios.

In addition, the seller surplus (SS) aggregates variable profits net of fixed costs, as in (10), over each seller's equilibrium decision. Each platform's profit (Π_f) comprises commission revenue on independent sales, own retail profit, and the logistics profits as in (17). Overall, the total welfare sums all as:

$$\text{W} = \text{CS} + \text{SS} + \Pi_{\text{Amz}} + \Pi_{\text{Wmt}} \tag{29}$$

7.1 Measuring the Welfare Effects of Vertical Integration

Vertical separation has both pro- and anti-competitive effects, so its welfare consequence is theoretically ambiguous. A role as an intermediary and own-product retailer respectively creates different impacts. On the beneficial side, separation removes the exclusivity of the high-quality logistics service and two cost-side impacts: inventory fragmentation, and the fixed cost of joining a competing platform.[48] The separation also removes the incentives to raise costs of sellers in order to divert sales to Amazon's own retail (Salop and Scheffman, 1983; Salinger, 1988).[49] On the other hand, separation removes the downward pressure that integration places on both the commission rate and the logistics fee. In addition, the separation introduces double marginalization that Amazon own retailer pays to the independent Amazon logistics operator (Spengler, 1950).

I re-solve the full game under the counterfactual separation regime: platforms set commissions and logistics fees, sellers choose entry and logistics, and prices adjust to equilibrium. However, two obstacles make an exact solution infeasible. First, as in many static entry games analyses, the equilibrium may not be unique. Second, computing the set of all potential Nash equilibria is infeasible. The ideal procedure would evaluate every profile of seller decisions and check profitable deviations from each profile for a given logistics fees and commission rates charge. With 1,839 independent sellers each choosing among eight alternatives, there are $8^{1,839}$ profiles, which is impossible to calculate. Therefore, I instead employ a rather simplified algorithm. For given logistics fees and commission rates, I let sellers move sequentially in a randomly drawn order.[50] I still allow full strategic responses of Amazon, Walmart and the separated Amazon logistics and solve them by employing fixed point iterations.

Panel (a) in Figure 10 shows the results. The vertical separation decreases consumer welfare and seller aggregate profits significantly by about 31.6% and 17.0%. Despite the separation Amazon compensates their profits by raising commission rates and own retail profits, resulting in 4.0% loss of their profit due to the separation. This profit excludes the independent FBA operator's profit that is 173% more than the profit of the integrated FBA. The clear winner is Walmart who earns 83.7% more profit because of the separation. The huge profits of indepdendent FBA operator and Walmart offset the losses, leading to 3.1% increase in social welfare.

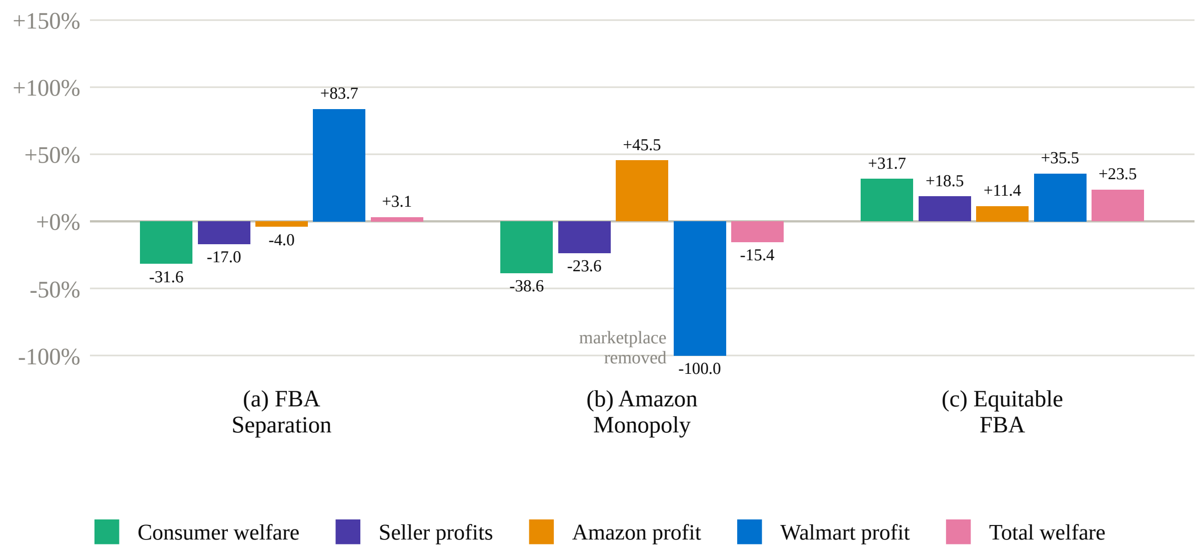
The increases in both logistics fee and commission rate dominate the pro-competitive effects of the vertical separation. The independent operator charges 48.3% more and Amazon marketplace charges 11.0pp more (from 15% to 26.0%) as shown in Figure 11. Walmart's best response is to increase their commission rates accordingly, from 15% to 24.5%. Highers fees and rates are passed through to consumers, so the average prices increase from \$66.05 to \$85.58 (29.6%). As consumer prices, commission rates, and the number of multihoming increases (5.2pp), Walmart commission revenue increase more than quadruple, which leads to substantial increase in the Walmart profit. Walmart's logistics, WFS, becomes not competitive to use, hence there is no seller who uses this

[48] I assume that the share of consumers holding Prime subscriptions, and hence with access to high-quality Amazon logistics service, is unchanged under separation. In the counterfactual regime, those consumers also receive high-quality Amazon logistics service on their Walmart orders. This can be interpreted as consumers subscribe for Prime membership program of the separated Amazon logistics.

[49] I let Amazon keep use the separated Amazon logistics in the separation regime. This abstracts away from contractual relationship between platforms and logistics providers in the counterfactual regime.

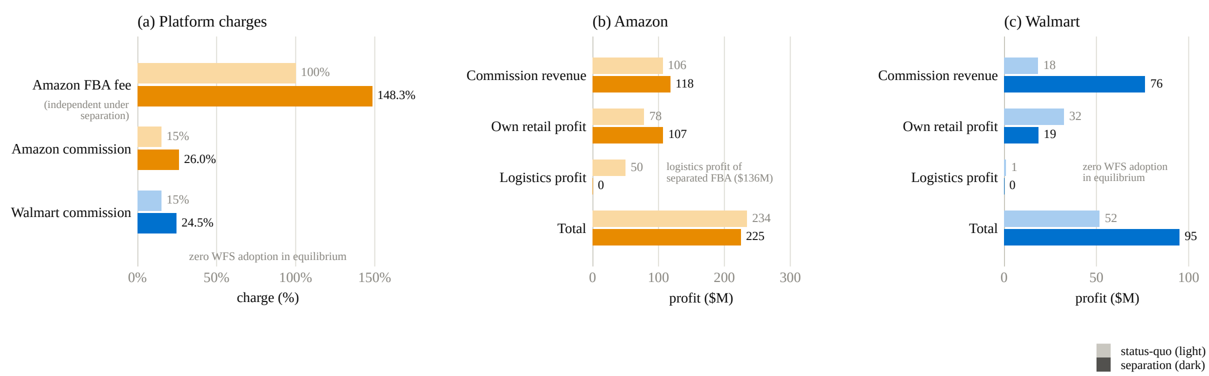
[50] Another approach to make an order of the decision is to rank independent sellers in the order of profitability as in Berry (1992).

Figure 10: Counterfactual Welfare Analyses



Notes. This figure shows the welfare results of the counterfactual analyses. All results are shown as% changes relative to the benchmark. Panel (a) makes Amazon's logistics, FBA, an independent operator and re-solves the full game. The profit of the independent FBA operator is included in total welfare but not in Amazon's profit. Panel (b) removes the Walmart marketplace and leaves Amazon as the monopoly platform. Panel (c) removes cost-frictions and exclusivity of Amazon logistics. Sellers can pool inventory and pay the same fixed costs as in the independent-logistics case while paying the observed Amazon logistics fees. Also, Prime subscribers can attain the same demand-side benefits on Walmart-side.

Figure 11: Market Outcomes of FBA Separation



Notes. This figure shows the changes in market outcomes of the FBA separation analysis. For each outcome, the upper light color bar shows the value of the integrated regime (status-quo). The lower dark color bar shows that of the counterfactual separation regime.

service. Interestingly, there are less and more sellers on Amazon and Walmart, which result in increase and decrease in own retail profits of Amazon and Walmart, respectively.

Overall, logistics integration is beneficial for consumers, even though the pro-competitive margins of separation, such as multihoming, non-exclusive quality, and inventory pooling, work. Separation raises logistics fees and commission rates by enough to offset these gains, and benefits Walmart substantially, which strategically raises its own commission in response too.

7.2 Amazon Monopoly

To what extent does a competing platform discipline the markup and commission incentive of a dominant platform, and thereby enhance the overall welfare? To address this quantitative question, I conduct a counterfactual simulation that removes the Walmart marketplace, together with Walmart's logistics service. Beyond e-commerce, the simulation has implications for an important market with a similar structure: app stores. In *Epic v. Google* (2025), the court ordered Google to open the Android app market to rival app stores.[51] By simulating a counterfactual in which Amazon is a monopolist, I measure the welfare impact of the presence of a competing platform. I implement the simulation by similarly following the procedure of the vertical separation counterfactual.[52]

Panel (b) of Figure 10 shows the welfare outcomes. The overall welfare loss is 15.4%. Consumer welfare falls by 38.6% and seller profits fall by 23.6%, while Amazon gains 45.5%.[53] Without the competing platform, Amazon raises its charges primarily through the logistics fee, by 40.6%, and raises its commission rate from 15% to 19.3%. The higher charges are passed through to consumers: average prices increase from \$66.05 to \$71.77 (8.7%), and FBA adoption rises to 98.3%; the marketplace consolidates into Amazon's own logistics. Notably, Amazon raises its fee and commission by less than in the vertical separation case, implying that the commission incentive still exerts downward pressure on charges. The increase in average prices is also thereby smaller than under vertical separation, yet the consumer welfare loss is larger.

To sum up, these results quantify the disciplining role of platform competition: a rival substantially constrains the dominant platform's fee and commission, and removing it transfers surplus from consumers and sellers to the platform.

7.3 Interoperability of Integrated Logistics

Reducing cost-side frictions and sharing the quality of Amazon logistics can be a policy target for enhancing welfare. In fact, there are active discussions on enforcing interoperability of a platform service (Bourreau and Krämer, 2023; Colangelo and Martinez, 2025) as a policy tool to foster platform competition. In this subsection, I examine a policy that mandates "equitable" interoperability (Crawford *et al.*, 2023), which completely removes the cost-side asymmetry and exclusivity of the quality. I also evaluate Amazon's multi-channel fulfillment service, which is partially, instead of fully, interoperable across platforms.

[51] https://www.nytimes.com/2024/10/07/technology/google-app-store-epic-games-anticompetitive.html

[52] To allow for an exit margin of each seller, I regard higher profits between Walmart single-homing with Walmart logistics and independent logistics as the exit value for each seller.

[53] Seller profits include the exit value leaving the marketplace. Operating profits of active sellers alone fall by 32.0%.

The counterfactual experiment of equitable Amazon logistics is as follows. When a seller multihomes using FBA, I allow the seller to pool inventory across channels and to pay the same fixed cost as under independent logistics. The seller also pays the same publicly posted Amazon logistics fee. To remove the demand-side exclusive quality, I assume that Prime subscribers attain the same demand-side quality on the Walmart side as well.

Panel (c) in Figure 10 shows the results. Removing cost-side frictions and demand-side exclusivity suggests room for enhancing welfare. Social welfare increases by about 23.5%, together with both consumer and seller welfare. To examine the mechanism behind this result, I conduct two decomposition analyses: the first removes only cost-side frictions, and the second removes only demand-side exclusivity. The results are shown in panels (b) and (c) of Figure A13. Removing cost-side frictions has a larger impact on social welfare (10.1%) than sharing exclusive quality (2.6%). The decomposition shows that the main welfare gains come from an increase in variety across platforms through multihoming.

I further conduct a counterfactual analysis of Amazon's multi-channel service, which is partially interoperable.[54] In this counterfactual, when a seller multihomes using Amazon logistics, the seller can pool inventory across platforms. However, the seller pays the multi-channel fee, which is publicly posted by Amazon, as a per-unit Walmart-side fee. The fixed costs of multihoming using Amazon logistics stay the same as estimated. Because Amazon's multi-channel service provides two-business-day shipping, I set the demand-side coefficient of using Amazon logistics on the Walmart side equal to that of Walmart logistics.

Panel (a) in Figure A13 shows that Amazon's multi-channel service has only a modest impact on welfare: consumer and social welfare increase by 1.5% and 0.9%, respectively. This suggests a room to improve welfare by further removing cost-side frictions and demand-side exclusivity.

8 Conclusion

In this research, I develop an empirical framework to evaluate the welfare effects of platforms' vertical integration of complementary services and apply it to logistics integration in the U.S. e-commerce competition between Amazon and Walmart. Integration brings a welfare trade-off. On the negative side, the integrating platform makes the service exclusive to (or favor) its own marketplace, drawing consumers and sellers away from rival platforms and weakening cross-platform competition. On the positive side, the platform, as an intermediary earning commissions, has an incentive to lower service fees to promote within-platform sales and commission profits.

I construct a novel dataset by linking product and seller data across the two platforms. Exploiting

[54] Walmart began allowing the use of the multi-channel service on May 15th, 2025. Most of the data period, which ends on June 4th, 2025, precedes this intervention; hence my analysis throughout assumes that the multi-channel service is not allowed. In this subsection, I instead examine the impact of introducing the multi-channel service through counterfactual analyses.

discontinuities in Amazon's logistics fee schedule, I estimate a regression discontinuity design and show that sellers facing higher fees are less likely to use Amazon logistics, more likely to join Walmart, and raise their prices on Amazon.

To measure the platforms' pricing incentives and the net welfare effects of integration, I develop and estimate a model in which consumers choose products across platforms, sellers make pricing, entry, and logistics decisions, and platforms set logistics fees and commission rates while also competing as own-product retailers. The estimates reveal that platforms could charge substantial markups on logistics fees, but the commission incentive offsets most of the markup. Separating Amazon logistics into an independent operator reduces consumer welfare because separation removes this countervailing pricing pressure, triggering increases in both logistics fees and commission rates that outweigh its pro-competitive effects. A counterfactual removing Walmart shows that the presence of a rival platform intensifies the commission incentive. In contrast, a policy mandating full interoperability—the same quality, fees, and entry costs regardless of the platform an order comes from—improves consumer and seller welfare. This means that although there are gains from platform's service integration, there are rooms for policy intervention for further enhance market welfare.

I conclude with future research directions. The first is applying the framework to other platform markets. The welfare trade-off in this paper is salient wherever dominant platforms integrate complementary services: Google and Apple operate payment systems for developers in their app marketplaces, and Google integrates its advertising exchange with its ad tools. These platforms exert vast influence on the economy and are subjects of antitrust cases, and the framework developed here provides a foundation for studying them. A second avenue is the dynamics of platform industries, whose trajectories are often described as winner-takes-all; studying how platform competition evolves jointly with integrated services would inform both our understanding of platform markets and the design of appropriate regulation.

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Appendix

A Stylized Model

In this section, I present a stylized model of e-commerce markets with integrated logistics to aggregate and delineate the economic forces introduced in the institutional background. The model highlights two main forces. On the seller side, the use of integrated logistics affects not only demand through fulfillment quality and platform promotion, but also costs by hindering sellers' ability to aggregate scale across platforms. This can generate cross-platform competition effects through economies of scale. On the platform side, because logistics are integrated with 1P retail and intermediation, the platform sets prices, commissions, and logistics fees while internalizing spillovers across these activities. This internalization generates both pro- and anti-competitive effects, motivating the empirical analysis.

Economic Environment There are two platforms, indexed by f, with $-f$ denoting the rival platform, and a set of single-product independent sellers indexed by $s \in \mathcal{S}^{\text{Ind}}$.[55] Each seller makes three decisions: whether to enter platform f ($e_{sf} \in \{0,1\}$), whether to use platform f's integrated logistics ($\ell_{sf} \in \{0,1\}$), and what retail price to charge $p_{sf} \in \mathbb{R}_+$. In addition to intermediating transactions for independent sellers, each platform also sells its own 1P product and operates its own logistics service. Accordingly, platform f has three decision variables: a 1P retail price ($p_f^{1\text{P}} \in \mathbb{R}_+$), an ad valorem commission rate ($\phi_f \in [0,1]$), and a per-unit logistics fee ($\text{fee}_f^{\ell} \in \mathbb{R}_+$).[56] There is also an independent logistics provider, indexed by o, which sets only a per-unit logistics fee fee_o^{ℓ}.

A.1 Seller Trade-offs, Logistics Choice, and Economies of Scale

I begin with the seller side of the model. Integrated logistics affects seller decisions through both demand and cost. On the demand side, using a platform's logistics service may improve fulfillment quality and may also confer platform-specific demand advantages, such as eligibility for prominent fulfillment-related badges. On the cost side, logistics choices affect per-unit fulfillment fees, the ability to aggregate scale across platforms, and the fixed costs of serving multiple marketplaces. These forces jointly shape seller pricing, logistics adoption, and multihoming decisions.

The total profit of seller s across platforms f is

$$\Pi_s = \sum_f \Big(\underbrace{p_{sf} \times Q_{sf}}_{\text{Revenue}} - \underbrace{TC_{sf}}_{\text{Total Costs}} \Big) \times \underbrace{e_{sf}}_{\text{Entry into } f} \tag{A.1}$$

where Q_{sf} is the sales quantity of seller s on platform f. TC_{sf} represents the total costs, which include both variable and fixed costs.

[55] In the stylized model, I assume each seller offers only a single product, so the product index j of the empirical model coincides with the seller index s, and I suppress the time index t. This single-product assumption is intended to illustrate key economic forces and will be relaxed to allow for multi-product sellers in the empirical model in Section 4.

[56] Although I assume platform-charged commission rates and logistics fees are uniform across products for illustrative purposes, in practice, these charges are uniform only across sellers but vary across products. Commission rates differ by product category, and fees are determined by a function mapping product size, weight, and category to shipping and storage costs. I introduce heterogeneity in the empirical model, where the product-specific fee is written fee_{jf}^{ℓ}, and exploit these variations for the empirical analyses.

The logistics choice ℓ_{sf} affects demand through three channels. First, it serves as a form of quality differentiation, since different logistics services provide different levels of fulfillment quality, such as delivery speed and reliability. Second, platforms may intervene on the demand side to promote their integrated services, for example by tying Prime eligibility to FBA usage. Third, logistics choice affects sellers' cost structures, leading them to adjust their retail prices, which in turn affects demand.

The total costs consist of variable and fixed costs:

$$TC_{sf}(\ell_{sf}, \bar{Q}_{sf}, W_s, Q_{sf}) = \underbrace{AVC_{sf}(\ell_{sf}, \bar{Q}_{sf}, W_s) \times Q_{sf}(\ell_{sf})}_{\text{Variable Costs } (VC_{sf})} + \underbrace{FC_{sf}(\ell_{sf})}_{\text{Fixed Costs}} \tag{A.2}$$

where AVC_{sf} is the average (or per-unit) variable cost and FC_{sf} is the fixed cost of joining platform f. Average variable cost depends on three objects. First, the logistics choice (ℓ_{sf}) affects variable costs because the logistics service directly charges per-unit fulfillment fees. The second argument comprises cost shifters, W_s, such as wholesale costs. Third, it depends on the seller's effective scale $\bar{Q}_{sf}$, reflecting the fact that both procurement terms and logistics contracts often improve with volume.[57]

The use of integrated logistics affects whether a seller can *aggregate* scale across platforms. I define the seller's effective scale on platform f as

$$\bar{Q}_{sf} := \begin{cases} Q_{sf} & \text{if } \ell_s = 1, \\ Q_{sf} + Q_{s,-f} & \text{if } \ell_s = 0, \end{cases} \tag{A.3}$$

where $\ell_s = \max\{\ell_{sf}, \ell_{s,-f}\}$ indicates whether seller s uses any platform's integrated logistics service. The idea is that once a seller adopts a platform-exclusive fulfillment system, inventory and operations become fragmented across platforms, preventing the seller from fully pooling scale. By contrast, when the seller relies on non-exclusive logistics, sales across platforms can be aggregated.[58]

Integrated logistics also affects fixed costs. On the focal platform, using the platform's own logistics service may reduce setup and operating burdens, lowering the fixed cost of participation. At the same time, because integrated logistics is platform-specific, it may require additional costs to expand to rival platforms relative to using an independent logistics provider; independent providers allow sellers to share fulfillment infrastructure across platforms more easily. Integrated logistics therefore creates a fixed-cost trade-off: it may facilitate participation on one platform while making multihoming more costly.

I investigate the channels that affect sellers' decisions and the trade-offs created by integrated logistics. First, I rewrite the total profit in (A.1) by substituting the total cost equation (A.2) as:

$$\Pi_s = \sum_f (p_{sf} Q_{sf} - VC_{sf} - FC_{sf}) \times e_{sf}$$

[57] For instance, sellers can leverage their sales volume to negotiate better deals with both logistics providers and manufacturers, as shown in Figure A10.

[58] In practice, integrated logistics need not be fully exclusive. For example, Amazon provides Multi-Channel Fulfillment (MCF) for orders placed outside Amazon. Yet, because Walmart had not accepted MCF for Walmart orders for most of the data period, I assume exclusivity in this paper. However, the non-exclusive case implies that the integrated platform may choose different prices and service quality for orders coming from rival platforms, which raises subsequent questions about the foreclosure through this interoperable logistics. I examine this issue through a counterfactual analysis.

Suppose seller s multihomes ($e_{sf} = e_{s,-f} = 1$) and profit functions are differentiable; we can then obtain the following first-order condition with respect to prices:

$$\begin{aligned}\frac{\partial \Pi_s}{\partial p_{sf}} = \underbrace{Q_{sf}}_{\text{Direct}} + \underbrace{p_{sf}\frac{\partial Q_{sf}}{\partial p_{sf}}}_{\text{Within-Platform Demand Loss}} + \underbrace{p_{s,-f}\frac{\partial Q_{s,-f}}{\partial p_{sf}}}_{\text{Cross-Platform Substitution}} \\ - \underbrace{\frac{\partial VC_{sf}}{\partial Q_{sf}}\frac{\partial Q_{sf}}{\partial p_{sf}}}_{\text{Within-Platform Cost Effects}} - \underbrace{\frac{\partial VC_{s,-f}}{\partial Q_{s,-f}}\frac{\partial Q_{s,-f}}{\partial p_{sf}}}_{\text{Cross-Platform Cost Spillover}} = 0 \end{aligned} \tag{A.4}$$

The first-order condition with respect to p_{sf} shows that pricing is not separable across platforms. Sellers not only consider standard within-platform factors but also internalize cross-platform interactions. Sellers consider business stealing effects across platforms and further take cost-side effects into account, which are linked via economies of scale.

By rearranging the terms in (A.4) and denoting $mc_{sf} = \frac{\partial VC_{sf}}{\partial Q_{sf}}$, we obtain the following pricing equations:

$$\begin{pmatrix} p_{sf} \\ p_{s,-f} \end{pmatrix} = \begin{pmatrix} mc_{sf} \\ mc_{s,-f} \end{pmatrix} - \underbrace{\begin{pmatrix} \frac{\partial Q_{sf}}{\partial p_{sf}} & \frac{\partial Q_{s,-f}}{\partial p_{sf}} \\ \frac{\partial Q_{sf}}{\partial p_{s,-f}} & \frac{\partial Q_{s,-f}}{\partial p_{s,-f}} \end{pmatrix}^{-1}}_{\Omega^{-1}} \begin{pmatrix} Q_{sf} \\ Q_{s,-f} \end{pmatrix} \tag{A.5}$$

A seller's adoption of a platform's integrated logistics ($\ell_{sf} = 1$) introduces four primary economic effects. First, a fee pass-through effect occurs, as the per-unit logistics fee fee^{ℓ}_f directly alters the seller's marginal cost, mc_{sf}. Second, adopting integrated logistics triggers distinct demand effects by potentially boosting sales on the focal platform ($Q_{sf} \uparrow$) while simultaneously reducing sales on the rival platform ($Q_{s,-f} \downarrow$), which consequently changes the demand substitution matrix, Ω. Third, the choice of logistics creates scale spillovers; because the seller's effective scale is modified, marginal costs across both platforms (mc_{sf} and $mc_{s,-f}$) may shift. Fourth, by altering both variable and fixed profits, it affects entry and multihoming decisions, which then feed back into equilibrium competition. Logistics choice therefore influences seller outcomes not only mechanically through fees, but also strategically through pricing, market participation, and scale aggregation.

A.2 Logistics Integration and Intermediation Incentives

This section discusses how vertical integration changes pricing incentives when the platform simultaneously operates retail, intermediation, and logistics with more details.[59]

I first present the model under logistics integration and then compare it to a benchmark model of logistics separation. In both regimes, platform f performs two roles in the product market: it acts as a 1P retailer and intermediates transactions for independent sellers. The difference is whether fulfillment is operated inside the platform or by an independent logistics provider.

[59] Gutierrez (2022) also consider Amazon's problem of price, commission and fee charges, yet my model has distinctions and extensions. I explicitly consider cost-side interactions of different supply chains, the effects of vertical integration on intermediation incentives, and cross-platform interactions.

A.2.1 Under Logistics Integration

Following the decomposition of platform profit in the empirical model, the profit function of platform f, (Π_f), splits into 1P retail profit (Π_f^{1P}), logistics profit (Π_f^{ℓ}), and commission profit (Π_f^{Com}):

$$\Pi_f = \Pi_f^{1P} + \underbrace{\Pi_f^{\ell} + \Pi_f^{Com}}_{\Pi_f^{Ind}} \tag{A.6}$$

$$\Pi_f^{1P} = \left(p_f^{1P} - mc_f^{1P}(mc_f^{\ell})\right) Q_f^{1P} \tag{A.7}$$

$$\Pi_f^{\ell} = \sum_{s \in \mathcal{S}^{Ind}} \left(\text{fee}_f^{\ell} - mc_f^{\ell}\right) \ell_{sf}\, e_{sf}\, Q_{sf} = \left(\text{fee}_f^{\ell} - mc_f^{\ell}\right) Q_f^{\ell} \tag{A.8}$$

$$\Pi_f^{Com} = \sum_{s \in \mathcal{S}^{Ind}} \phi_f\, p_{sf}\, e_{sf}\, Q_{sf} = \phi_f R_f^{Com} \tag{A.9}$$

where p_f^{1P}, mc_f^{1P}, and Q_f^{1P} denote the 1P price, retail marginal cost, and sales quantity in platform marketplace f; $Q_f^{\ell} \equiv \sum_s \ell_{sf} e_{sf} Q_{sf}$ is fulfilled volume; and $R_f^{Com} \equiv \sum_s p_{sf} e_{sf} Q_{sf}$ is the commission base.[60] When it comes to the 1P profit, the platform sets its own retail price and earns a margin equal to the difference between that price and its retail marginal cost. Because the platform fulfills its own retail orders using its integrated logistics service, its 1P retail cost (mc_f^{1P}) depends directly on the underlying logistics cost (mc_f^{ℓ}).

The profit earned from independent sellers, Π_f^{Ind}, has two components: logistics profits and commission revenues. In the logistics market chain, platforms charge a unit fee (fee_f^{ℓ}) to a seller and fulfillment incurs mc_f^{ℓ} to the platform. Whenever a seller enters the platform and adopts the integrated logistics service, the platform fulfills that seller's orders and earns a logistics margin on the resulting volume. In addition, the platform charges an ad valorem commission on independent sellers' transactions, so commission revenue is proportional to independent seller revenue.

Following the decision timing in Figure 5, I take partial differentiation with respect to 1P retail prices and total differentiation with respect to the logistics fee and commission rate as:[61]

$$\frac{\partial \Pi_f}{\partial p_f^{1P}} = Q_f^{1P} + \left(p_f^{1P} - mc_f^{1P}(mc_f^{\ell})\right) \frac{\partial Q_f^{1P}}{\partial p_f^{1P}} + \left(\text{fee}_f^{\ell} - mc_f^{\ell}\right) \frac{\partial Q_f^{\ell}}{\partial p_f^{1P}} + \phi_f \frac{\partial R_f^{Com}}{\partial p_f^{1P}} = 0 \tag{A.10}$$

$$\frac{\mathrm{d}\Pi_f}{\mathrm{d}\text{fee}_f^{\ell}} = \left(p_f^{1P} - mc_f^{1P}(mc_f^{\ell})\right) \frac{\mathrm{d}Q_f^{1P}}{\mathrm{d}\text{fee}_f^{\ell}} + Q_f^{\ell} + \left(\text{fee}_f^{\ell} - mc_f^{\ell}\right) \frac{\mathrm{d}Q_f^{\ell}}{\mathrm{d}\text{fee}_f^{\ell}} + \phi_f \frac{\mathrm{d}R_f^{Com}}{\mathrm{d}\text{fee}_f^{\ell}} = 0 \tag{A.11}$$

$$\frac{\mathrm{d}\Pi_f}{\mathrm{d}\phi_f} = \left(p_f^{1P} - mc_f^{1P}(mc_f^{\ell})\right) \frac{\mathrm{d}Q_f^{1P}}{\mathrm{d}\phi_f} + \left(\text{fee}_f^{\ell} - mc_f^{\ell}\right) \frac{\mathrm{d}Q_f^{\ell}}{\mathrm{d}\phi_f} + R_f^{Com} + \phi_f \frac{\mathrm{d}R_f^{Com}}{\mathrm{d}\phi_f} = 0 \tag{A.12}$$

To understand pricing incentives along the supply chain, I derive the platform's pricing equations

[60] For simplicity, I assume the platform is a single-product seller in a stylized model, which will be relaxed in the empirical model. Because the fee is uniform here, the empirical model's fulfillment revenue base satisfies $R_f^{\ell} = \overline{\text{fee}}_f^{\ell} Q_f^{\ell}$; the stylized model works directly with the volume Q_f^{ℓ}.

[61] Note that the terms $\frac{\partial \Pi_f}{\partial p_f^{1P}} \frac{\mathrm{d}p_f^{1P}}{\mathrm{d}\text{fee}_f^{\ell}}$ and $\frac{\partial \Pi_f}{\partial p_f^{1P}} \frac{\mathrm{d}p_f^{1P}}{\mathrm{d}\phi_f}$ are zero by the envelope theorem (i.e., $\frac{\partial \Pi_f}{\partial p_f^{1P}} = 0$ in the pricing stage) and hence omitted.

Table A1: Definitions of Margin, (Semi-)Elasticity and Diversion Ratio Terms

Measure	Notation	Definition	Expected Sign
1P Margin	μ_f^{1P}	$p_f^{1P} - mc_f^{1P}$	(+)
1P Price Semi-elasticity	$\sigma_{f,p}^{1P}$	$-\dfrac{\partial Q_f^{1P}/\partial p_f^{1P}}{Q_f^{1P}}$	(+)
1P to Commission-Base Diversion	$D_{f,p}^{R,\mathrm{Com}}$	$-\dfrac{\partial R_f^{\mathrm{Com}}/\partial p_f^{1P}}{\partial Q_f^{1P}/\partial p_f^{1P}}$	(+)
1P to Logistics Diversion	$D_{f,p}^{\ell}$	$-\dfrac{\partial Q_f^{\ell}/\partial p_f^{1P}}{\partial Q_f^{1P}/\partial p_f^{1P}}$	(+)
Logistics Margin	μ_f^{ℓ}	$\mathrm{fee}_f^{\ell} - mc_f^{\ell}$	(+)
Fee Semi-elasticity	$\sigma_{f,\mathrm{fee}}^{\ell}$	$-\dfrac{\mathrm{d}Q_f^{\ell}/\,\mathrm{dfee}_f^{\ell}}{Q_f^{\ell}}$	(+)
Logistics to 1P Diversion	$D_{f,\mathrm{fee}}^{1P}$	$-\dfrac{\mathrm{d}Q_f^{1P}/\,\mathrm{dfee}_f^{\ell}}{\mathrm{d}Q_f^{\ell}/\,\mathrm{dfee}_f^{\ell}}$	(+)
Logistics to Commission-Base Diversion	$D_{f,\mathrm{fee}}^{R,\mathrm{Com}}$	$-\dfrac{\mathrm{d}R_f^{\mathrm{Com}}/\,\mathrm{dfee}_f^{\ell}}{\mathrm{d}Q_f^{\ell}/\,\mathrm{dfee}_f^{\ell}}$	(−)
Commission Semi-elasticity of the Commission Base	$\sigma_{f,\phi}^{R,\mathrm{Com}}$	$-\dfrac{\mathrm{d}R_f^{\mathrm{Com}}/\,\mathrm{d}\phi_f}{R_f^{\mathrm{Com}}}$	(+)
Commission-Base to 1P Diversion	$D_{f,\phi}^{1P}$	$-\dfrac{\mathrm{d}Q_f^{1P}/\,\mathrm{d}\phi_f}{\mathrm{d}R_f^{\mathrm{Com}}/\,\mathrm{d}\phi_f}$	(+)
Commission-Base to Logistics Diversion	$D_{f,\phi}^{\ell}$	$-\dfrac{\mathrm{d}Q_f^{\ell}/\,\mathrm{d}\phi_f}{\mathrm{d}R_f^{\mathrm{Com}}/\,\mathrm{d}\phi_f}$	(−)

Notes. This table shows the economic measure, notation, definition and expected sign of terms in (A.13), (A.14), and (A.15). The commission base is R_f^{Com}, defined in (A.9). Margins measure per-unit profits in each supply chain, semi-elasticities determine the standard markup components, and diversion ratios capture cross-chain spillovers that arise because the platform simultaneously operates retail, marketplace, and logistics services. Under the standard monopolistic pricing assumption, $\mathrm{d}R_f^{\mathrm{Com}}/\,\mathrm{d}\phi_f < 0$ holds as shown in Appendix A.2.4.

by rearranging the first-order conditions:

$$p_f^{1\mathrm{P}} = mc_f^{1\mathrm{P}}(mc_f^{\ell}) + (\sigma_{f,p}^{1\mathrm{P}})^{-1} + \overbrace{\underbrace{\phi_f D_{f,p}^{R,\mathrm{Com}}}_{(+)} + \underbrace{\mu_f^{\ell} D_{f,p}^{\ell}}_{(+)}}^{\text{Cross-chain Internalization}} \tag{A.13}$$

$$\mathrm{fee}_f^{\ell} = mc_f^{\ell} + (\sigma_{f,\mathrm{fee}}^{\ell})^{-1} + \overbrace{\underbrace{\mu_f^{1\mathrm{P}} D_{f,\mathrm{fee}}^{1\mathrm{P}}}_{(+)} + \underbrace{\phi_f D_{f,\mathrm{fee}}^{R,\mathrm{Com}}}_{(-)}}^{\text{Cross-chain Internalization}} \tag{A.14}$$

$$\phi_f = (\sigma_{f,\phi}^{R,\mathrm{Com}})^{-1} + \overbrace{\underbrace{\mu_f^{1\mathrm{P}} D_{f,\phi}^{1\mathrm{P}}}_{(+)} + \underbrace{\mu_f^{\ell} D_{f,\phi}^{\ell}}_{(-)}}^{\text{Cross-chain Internalization}} \tag{A.15}$$

where the definitions and expected signs of economic objects are introduced in Table A1. Each pricing rule consists of three components: marginal cost (mc), the standard markup term determined by demand elasticities (σ), and additional internalization terms, profit margin (μ) and diversion ratios (D), reflecting how the platform accounts for the effects of pricing decisions across different supply chains.

Because of vertical integration, the platform internalizes how prices, logistics fees, and commission rates affect outcomes across the different supply chains. Platform pricing therefore reflects a key trade-off arising from the dual relationship with independent sellers. On the one hand, the platform competes with independent sellers as a 1P retailer and therefore has an incentive to steal business from them. On the other hand, the platform earns commissions and logistics fees from independent sellers' transactions, which creates an incentive to promote their sales.

Logistics integration generates different pricing incentives for 1P retail prices and commission rates. Consider first the 1P retail pricing in (A.13). When the platform raises its own retail price, some demand is diverted toward independent sellers. Under integration, part of that diverted demand generates logistics profits in addition to commission revenue. This creates an additional incentive to soften 1P price competition.

In contrast, as shown in (A.15), increasing the commission rate raises the marginal costs of independent sellers. Sellers respond by increasing prices, which reduces their sales and the associated demand for logistics services. Because the platform internalizes this loss in logistics profit, integration creates downward pressure on commission rates. Both effects also enter the logistics fee pricing rule, generating offsetting pricing pressures on logistics fees.

A.2.2 Under Logistics Separation

I next consider a benchmark regime with vertical separation. The profit functions of the logistics-segregated platform f and the independent logistics operator o are

$$\begin{aligned}
\Pi_f^{1P} &= \left(p_f^{1P} - mc_f^{1P}(\text{fee}_o^{\ell})\right) Q_f^{1P} \\
\Pi_f^{\text{Com}} &= \phi_f \sum_{s \in \mathcal{S}^{\text{Ind}}} p_{sf}\, e_{sf}\, Q_{sf} = \phi_f R_f^{\text{Com}} \\
\Pi_o^{\ell} &= \left(\text{fee}_o^{\ell} - mc_o^{\ell}\right) \sum_f \sum_{s \in \mathcal{S}^{\text{Ind}}} e_{sf}\, Q_{sf} = \left(\text{fee}_o^{\ell} - mc_o^{\ell}\right) \sum_f Q_{of}^{\ell} = \left(\text{fee}_o^{\ell} - mc_o^{\ell}\right) Q_o^{\ell}
\end{aligned}$$

There are three main changes from the profit functions of the vertically integrated case. First, the platform does not internalize the profit from the logistics market. Second, the platform's 1P retail cost directly depends on the fee charged by the independent logistics operator, fee_o^{ℓ}, instead of the logistics cost mc_o^{ℓ}. Lastly, the logistics operator internalizes cross-platform sales, as its service is not exclusive to platform f.

As in the vertically integrated case, I use and arrange the first-order conditions to attain the following pricing equations:

$$p_f^{1P} = mc_f^{1P}(\text{fee}_o^{\ell}) + (\sigma_{f,p}^{1P})^{-1} + \phi_f D_{f,p}^{R,\text{Com}} \tag{A.16}$$

$$\phi_f = (\sigma_{f,\phi}^{R,\text{Com}})^{-1} + \mu_f^{1P} D_{f,\phi}^{1P} \tag{A.17}$$

$$\text{fee}_o^{\ell} = mc_o^{\ell} + (\sigma_{o,\text{fee}}^{\ell})^{-1} \tag{A.18}$$

Under separation, the platform no longer internalizes spillovers into logistics profits, while the logistics operator sets fees to maximize its own profit and internalizes fulfillment demand across platforms.

Vertical integration reduces double marginalization in 1P retail. This can be seen by comparing the retail-cost terms in the integrated and separated pricing equations, (A.13) and (A.16). Under vertical integration, as shown in (A.13), the platform's retail cost depends directly on the underlying logistics cost. By contrast, under vertical separation in (A.16), the platform's retail cost depends on the logistics fee charged by an independent logistics operator. As a result, separation introduces an additional markup through the logistics provider, which vertical integration eliminates.

By contrast, the effect of integration on logistics fee levels is theoretically ambiguous. Under separation, the independent logistics provider internalizes demand substitution across platforms: if a fee increase raises consumer prices on one platform, some demand may shift to a rival platform that the same logistics provider also serves. This dampens the pricing pressure coming from the demand response to fee increases and can result in higher markups. Under integration, however, the platform may strengthen demand for its logistics service by attaching platform-specific benefits, such as Prime eligibility, to adoption of integrated logistics. These demand-side interventions also reduce the elasticity of demand for logistics and can lead to higher markups. Because separation broadens the logistics provider's scope while integration may strengthen platform-specific demand for logistics, the net effect on logistics markups cannot be signed a priori.

A.2.3 Welfare Implications and Empirical Measurements

Each agent faces welfare trade-offs under logistics integration. To be specific, consumer welfare reflects a trade-off between prices and fulfillment quality, while sellers face a trade-off between demand expansion and the cost changes of using integrated logistics. A platform's profit is determined by how it balances these trade-offs and shapes market equilibrium through its pricing strategies, which are influenced by the degree of internalization of cross-chain effects and competitive pressure from its rival platform $-f$. Therefore, the key empirical objects to quantify are consumer utility over prices and fulfillment services, together with seller cost structures that include economies of scale and multihoming costs interacting with fulfillment choices. Recovering consumer and seller primitives allows us to measure how responsive sellers are to commission rates and logistics fees, and thereby the platform's pricing incentives, which are critical for counterfactual exercises.

Given these trade-offs, the model suggests several pro-competitive channels of logistics integration. First, integration eliminates double marginalization in 1P retail by replacing an upstream logistics fee with the platform's own underlying logistics cost. This tends to lower the cost base of 1P retail. Second, integration may create downward pressure on commission rates. Because higher commissions reduce independent sellers' sales and therefore reduce integrated logistics usage, the platform internalizes a cost of raising commissions that is absent under separation. Third, integrated logistics may reduce platform-specific setup costs for sellers and thereby facilitate entry into the focal marketplace. To the extent that this expands seller participation, integration can intensify competition on that platform. Fourth, exclusivity of the integrated logistics removes the cross-platform internalization of fee increases by an independent logistics provider, which may otherwise soften price competition between platforms.

There are also anti-competitive channels. First, integration can soften 1P retail competition. When the platform raises its own retail price, some demand is diverted toward independent sellers, and, under integration, part of that diverted demand is recaptured through commissions and logistics profits. Second, integration may support exclusionary demand-side conduct. If the platform grants exclusive consumer-facing benefits to sellers using its own logistics service, demand for integrated logistics becomes less elastic, allowing the platform to charge higher effective markups. Third, integrated logistics can directly affect market structure by fragmenting seller scale and raising the cost of operating across platforms. Because platform-specific fulfillment limits the ability to pool inventory and fixed costs, integration can discourage multihoming and soften cross-platform competition.

Therefore, the welfare effects of logistics integration demand empirical investigation. To quantify them, I assemble a dataset revealing the relationship between logistics usage and the cross-platform behavior of sellers, and I develop an empirical model with multi-platform equilibrium interactions in Section 4. Prior to building the model, I present descriptive evidence consistent with the stylized model, including results from regression discontinuity analyses in the upcoming Sections 3 and 3.3.1.

A.2.4 Commission Rate (ϕ) and the Commission Base

Let R_f^{Com} denote the commission base on platform f, that is, total independent-seller revenue. Suppose sellers choose prices p, and demand depends on prices. The commission base can be written as

$$R_f^{\text{Com}} = p \cdot Q(p).$$

When the platform increases the commission rate ϕ_f, sellers face higher marginal costs (as the commission acts like an ad valorem tax). Sellers adjust prices p, which in turn changes demand. Therefore R_f^{Com} changes through both price and quantity responses. Differentiating the base with respect to the commission rate yields

$$\frac{\mathrm{d}R^{\text{Com}}}{\mathrm{d}\phi} = \frac{\mathrm{d}p}{\mathrm{d}\phi}Q + p\frac{\mathrm{d}Q}{\mathrm{d}p}\frac{\mathrm{d}p}{\mathrm{d}\phi}.$$

Factoring out $\frac{\mathrm{d}p}{\mathrm{d}\phi}Q$ gives

$$\frac{\mathrm{d}R^{\text{Com}}}{\mathrm{d}\phi} = \frac{\mathrm{d}p}{\mathrm{d}\phi}Q\left(1 + \frac{p}{Q}\frac{\mathrm{d}Q}{\mathrm{d}p}\right),$$

where $\frac{p}{Q}\frac{\mathrm{d}Q}{\mathrm{d}p} = -\varepsilon$ and ε is the price elasticity of demand. Substituting this expression yields

$$\frac{\mathrm{d}R^{\text{Com}}}{\mathrm{d}\phi} = \frac{\mathrm{d}p}{\mathrm{d}\phi}Q(1-\varepsilon).$$

Therefore, the elasticity of demand (ε) determines the sign of the commission-base response to commission rate increases. When demand is elastic, $1-\varepsilon < 0$, higher commissions increase seller prices and reduce quantity substantially, implying

$$\frac{\mathrm{d}R^{\text{Com}}}{\mathrm{d}\phi} < 0.$$

On the other hand, when demand is inelastic, $1-\varepsilon > 0$, the price increase dominates the quantity reduction, implying

$$\frac{\mathrm{d}R^{\text{Com}}}{\mathrm{d}\phi} > 0.$$

Under the monopolistic pricing assumption, profit maximization is achieved on the elastic part of demand. This implies that the expected sign of $\frac{\mathrm{d}R^{\text{Com}}}{\mathrm{d}\phi}$ is negative.

A.3 Online and Offline Retails and the Recovery of Marginal Costs

The baseline model focuses on competition between the online marketplaces. Walmart, however, operates an extensive brick-and-mortar network and prices its online catalog while internalizing how online prices divert demand to its own stores. This subsection extends the stylized model of Section A.2 to let Walmart operate an offline retail channel, and shows precisely how the marginal cost in the original model absorbs this cross-channel substitution.

Walmart's Multi-Channel Profit Suppose $f = \text{Wmt}$ and add a brick-and-mortar retail channel alongside online 1P retail, the online marketplace for independent sellers, and logistics. Let $\mu_{\text{Wmt}}^{1\text{P}} = p_{\text{Wmt}}^{1\text{P}} - mc_{\text{Wmt}}^{1\text{P}}$ and $\mu_{\text{Wmt}}^{B} = p_{\text{Wmt}}^{B} - mc_{\text{Wmt}}^{B}$ denote the online and offline retail margins, where the superscript B indexes the offline (brick-and-mortar) channel. Walmart's profit is

$$\Pi_{\text{Wmt}} = \underbrace{\mu_{\text{Wmt}}^{1\text{P}}\,Q_{\text{Wmt}}^{1\text{P}}}_{\text{online 1P}} + \underbrace{\mu_{\text{Wmt}}^{B}\,Q_{\text{Wmt}}^{B}}_{\text{offline 1P}} + \underbrace{\mu_{\text{Wmt}}^{\ell}\,Q_{\text{Wmt}}^{\ell} + \phi_{\text{Wmt}}R_{\text{Wmt}}^{\text{Com}}}_{\text{independent sellers}}. \tag{A.19}$$

The two retail channels are substitutes, so an increase in the online price weakly raises offline demand, $\partial Q^{B}_{\text{Wmt}}/\partial p^{1\text{P}}_{\text{Wmt}} \geq 0$.

Online Pricing under Multi-Channel Retail Differentiating (A.19) with respect to the online 1P price—the price inverted on the supply side—yields one additional term relative to the single-channel case:

$$Q^{1\text{P}}_{\text{Wmt}} + \mu^{1\text{P}}_{\text{Wmt}} \frac{\partial Q^{1\text{P}}_{\text{Wmt}}}{\partial p^{1\text{P}}_{\text{Wmt}}} + \underbrace{\mu^{B}_{\text{Wmt}} \frac{\partial Q^{B}_{\text{Wmt}}}{\partial p^{1\text{P}}_{\text{Wmt}}}}_{\text{offline recapture}} + \mu^{\ell}_{\text{Wmt}} \frac{\partial Q^{\ell}_{\text{Wmt}}}{\partial p^{1\text{P}}_{\text{Wmt}}} + \phi_{\text{Wmt}} \frac{\partial R^{\text{Com}}_{\text{Wmt}}}{\partial p^{1\text{P}}_{\text{Wmt}}} = 0. \tag{A.20}$$

Define the diversion ratio from online 1P retail to the offline channel, following the convention of Table A1,

$$D^{B}_{\text{Wmt},p} \equiv -\frac{\partial Q^{B}_{\text{Wmt}}/\partial p^{1\text{P}}_{\text{Wmt}}}{\partial Q^{1\text{P}}_{\text{Wmt}}/\partial p^{1\text{P}}_{\text{Wmt}}} \geq 0. \tag{A.21}$$

Rearranging (A.20) gives the online pricing equation

$$p^{1\text{P}}_{\text{Wmt}} = mc^{1\text{P}}_{\text{Wmt}} + (\sigma^{1\text{P}}_{\text{Wmt},p})^{-1} + \overbrace{\underbrace{\phi_{\text{Wmt}} D^{R,\text{Com}}_{\text{Wmt},p}}_{(+)} + \underbrace{\mu^{\ell}_{\text{Wmt}} D^{\ell}_{\text{Wmt},p}}_{(+)}}^{\text{intra-platform internalization}} + \overbrace{\underbrace{\mu^{B}_{\text{Wmt}} D^{B}_{\text{Wmt},p}}_{(+)}}^{\text{offline recapture}}. \tag{A.22}$$

The only difference from the integrated 1P pricing rule (A.13) is the final, nonnegative term. It reflects that Walmart prices online above the single-channel optimum because a fraction of the demand lost to an online price increase is recaptured in its own stores at margin μ^{B}_{Wmt}.

Implication for Marginal-Cost Recovery Suppose the estimated model omits the offline channel and therefore recovers the online marginal cost, $\widehat{mc}^{1\text{P}}_{\text{Wmt}}$, from the pricing rule (A.13) rather than (A.22):

$$\widehat{mc}^{1\text{P}}_{\text{Wmt}} = p^{1\text{P}}_{\text{Wmt}} - (\sigma^{1\text{P}}_{\text{Wmt},p})^{-1} - \phi_{\text{Wmt}} D^{R,\text{Com}}_{\text{Wmt},p} - \mu^{\ell}_{\text{Wmt}} D^{\ell}_{\text{Wmt},p}. \tag{A.23}$$

Substituting the true price (A.22) into (A.23), and holding the demand derivatives at their true values, the recovered marginal cost satisfies

$$\widehat{mc}^{1\text{P}}_{\text{Wmt}} = mc^{1\text{P}}_{\text{Wmt}} + \mu^{B}_{\text{Wmt}}\, D^{B}_{\text{Wmt},p} \;\geq\; mc^{1\text{P}}_{\text{Wmt}}. \tag{A.24}$$

The recovered online marginal cost equals the true marginal cost plus the cross-channel internalization term $\mu^{B}_{\text{Wmt}} D^{B}_{\text{Wmt},p}$—the per-unit offline margin times the share of marginally lost online demand recaptured in stores.

Note that this analysis extends to independent sellers' pricing incentives when they have an alternative retail channel. By the same logic, the marginal costs recovered from the demand estimates and Bertrand-Nash pricing conduct would also absorb the pricing pressure originating from the alternative channel.

B Data Construction

B.1 full-category panel

Table A2: Summary of Data

Data Source	Description	Platform
Keepa API	Historical product/seller data and contact information	Amazon
Jungle Scout	Sales estimates	
DataSpark API	Historical product/seller data and sales estimates	Walmart
BlueCart API	Seller contact information	
Numerator	Expenditure information	Multi

Notes. Sales estimates will be obtained for the specific category used in the structural analysis.

The primary source of data is Keepa.com, whose API grants access to historical data on products, sellers, and their offers within the Amazon marketplace.[62] For instance, it enables us to track the historical price of a product by each seller and identify which offers Amazon has featured over time. Notably, it includes information on whether a seller has opted for Amazon's fulfillment service for shipping and if an offer is Prime eligible. Additionally, it provides the seller's address, historical product and seller ratings, shipping costs, historical sales rank, product characteristics, and fulfillment costs.

Utilizing the Keepa API, I have initially retrieved a list of bestsellers from 9 product categories.[63] Subsequently, I have requested product and seller information for these bestsellers through the API. Then, I match listings on Amazon with those on other retail channels by using the Universal Product Code (UPC) of a product. A UPC is a unique code assigned to each product or variation thereof, meaning that if two products share the same UPC, they are identical. I used both BlueCart API and DataSpark API in order to search for product info through UPCs.

Furthermore, the DataSpark API provides historical information from Walmart side, which is similar to data from Keepa API about Amazon side. However, the historical variations of Walmart prices retrieved via DataSpark are far less frequent than those of Keepa on Amazon products. I use BlueCart API service that scrapes seller information from Walmart marketplace that contains the address and contact information.

B.2 Matching Sellers

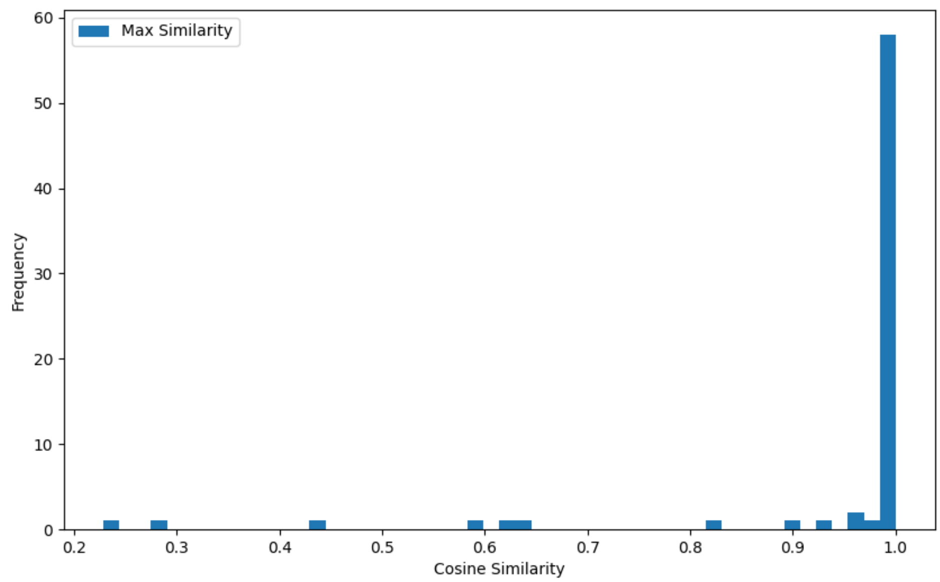
In both Amazon and Walmart marketplaces, seller information such as name, phone number, email, and physical address is displayed. A key institutional fact is that this contact information is used for business and tax verification purposes in both marketplaces. Therefore, this infromation is useful to identify the same sellers across these platforms.

To identify identical sellers operating across platforms, I restrict our focus to the set of products j that are co-listed on both Amazon and Walmart. Let $S^f(j)$ denote the set of sellers offering product

[62] Data from this source have been utilized in previous research, such as Chen and Tsai (forthcoming); Reimers and Waldfogel (2021); Lee and Musolff (2025).

[63] I follow the category definition in Amazon and categories are Appliances, Electronics, Office Products, Tools & Home Improvement, Home & Kitchen, Sports & Outdoors, Pet Supplies, Beauty & Personal Care, Clothing, Shoes & Jewelry

Figure A1: Distribution of Cosine Similarity of Phone-number Matched Sellers



Notes. This figure shows the histogram of the cosine similarity between Amazon and Walmart sellers who are pairwise matched by their phone numbers.

j on platform $f \in \{\text{Amz}, \text{Wmt}\}$. We establish a match between an Amazon seller $s \in S^{\text{Amz}}(j)$ and a Walmart seller $s' \in S^{\text{Wmt}}(j)$ if they share the exact same phone number, or if their registered business names or physical addresses are identical. To account for variations in text and quantify the closeness of these matches, I employ a semantic similarity measure. Specifically, I utilize a pre-trained Large Language Model, Sentence-BERT (Reimers and Gurevych, 2019), to generate embeddings of the seller profiles and calculate the cosine similarity between them.

I validate this approach by examining the cosine similarity distribution specifically for the subset of sellers matched via phone numbers, which serves as a ground-truth baseline. The results are shown in Figure A1. I verify that almost every phone-number matched sellers can be matched via the embedding-based method.

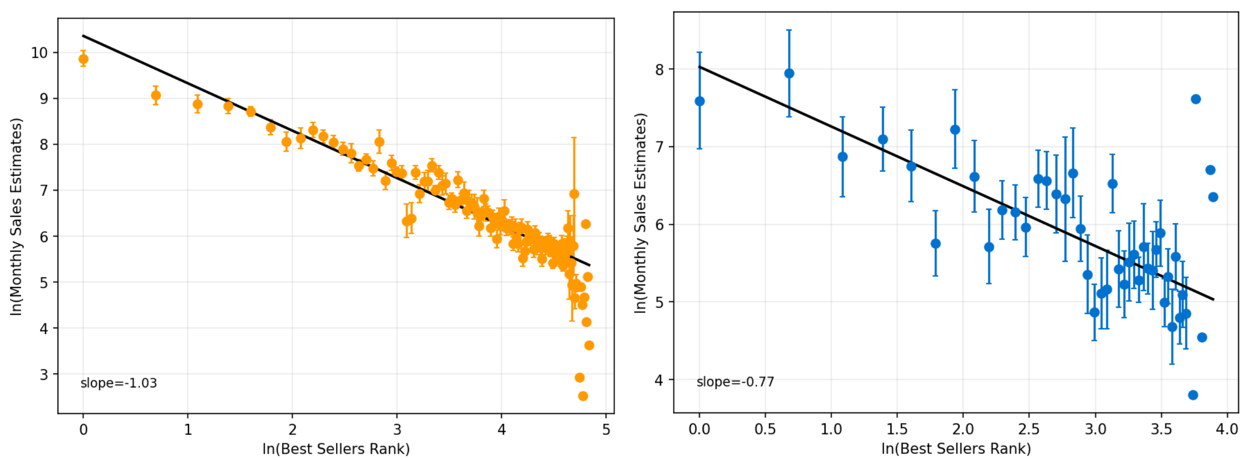
B.3 kitchen appliance panel

I web scrape bestsellers of each subcategory (e.g., air fryer) on both Amazon and Walmart and use API extensions to gather further details by weekly. I use keyword search on Amazon and Walmart by giving each subcategory as a kewyord and scrape appeared products. I sort products by bestsellers and featured and scrape them both.

I use Jungle Scout sales estimates for the designated category to obtain proxy sales data. Jungle Scout is an intelligent service provider for Amazon sellers that uses actual sales records to convert best seller ranks into sales estimates. This service is also used by Yu (2024). For the Walmart-side sales proxy, I similarly use sales estimates provided by Bizmetrica.

To check the validity of the sales estimates obtained through the services, I inspect the relationship between the sales estimates and best seller ranks. A product's best seller rank indicates its relative position when products are sorted by sales volume on either platform. Figure A2 shows these relationships. There is a strong negative relationship on both platforms, although the Walmart side is noisier. This verifies that the sales estimates generally align with best seller ranks across each subcategory.

Figure A2: Bestseller Ranks and Sales Estimates



(a) Amazon

(b) Walmart

Notes. This figure shows the relationship between the log of monthly sales estimates and the log of best seller ranks on Amazon and Walmart. Monthly sales estimates are attained through JungleScout and Bizmetrica API for Amazon and Walmart-side. The relationship is strongly negative on both platforms, although the Walmart side is noisier.

B.4 Regression Analysis of Multihoming on FBA

I regress the following model:

$$\text{Multihome}_{st} = \alpha^{FBA}\text{FBA}_{st} + \alpha_t + \alpha_s + u_{st}$$

where FBA_{st} is the dummy indicating seller s uses FBA at month t. α_s and α_t are seller and month fixed effects, respectively.

Table A3: Regressing Multihoming on FBA

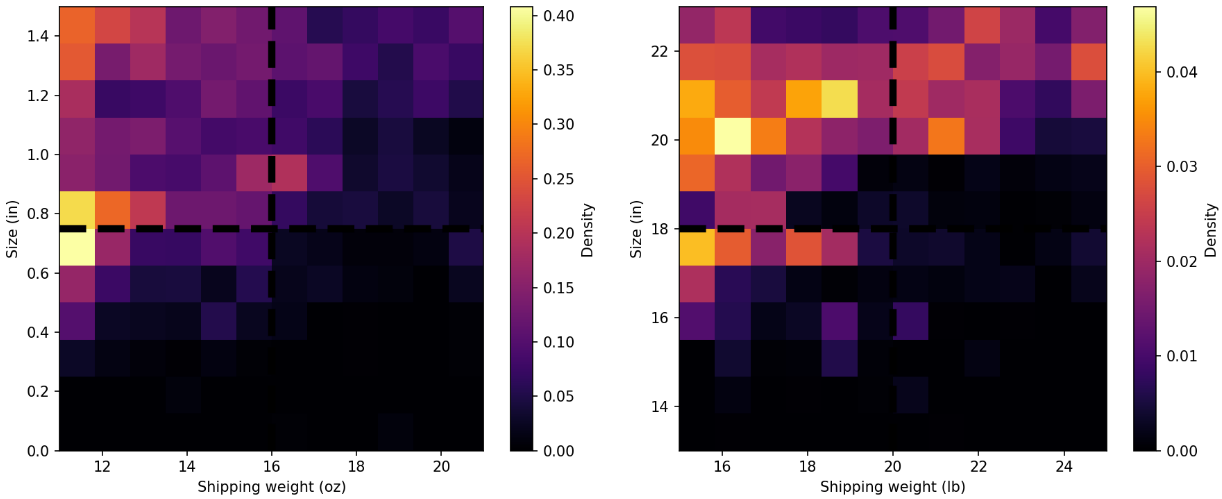
	OLS			WLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables			Multihome_{st}			
FBA_{st}	-0.0097***	-0.0110***	-0.0020**	-0.1602***	-0.1660***	-0.0110**
	(0.001)	(0.001)	(0.001)	(0.021)	(0.022)	(0.005)
Intercept	0.0330***			0.2214***		
	(0.001)			(0.021)		
R-squared	0.001	0.002	0.600	0.041	0.050	0.809
Time FE	No	Yes	Yes	No	Yes	Yes
Seller FE	No	No	Yes	No	No	Yes
Weighted	No	No	No	Yes	Yes	Yes
Observations	882,210	882,210	882,210	882,210	882,210	882,210

Notes. This table shows the estimates from the regression analysis of multihoming on FBA with fixed effects. Multihoming is defined as an indicator of seller s appears on Walmart at month t. The number of product offerings on Amazon is used for running weighted least square estimation. The simple and weighted averages of the dependent variable are 0.028 and 0.112. Standard errors clustered at seller-level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3 shows the results and confirms that the negative correlation between FBA and multihoming, holding fixed effects.

C More on Regression Discontinuity Analysis

Figure A3: Distributions of Density Estimates Around Product Size-Tier Cutoffs

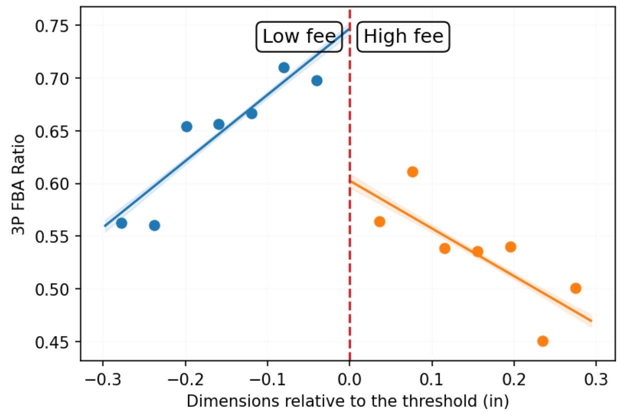


(a) Small to Large

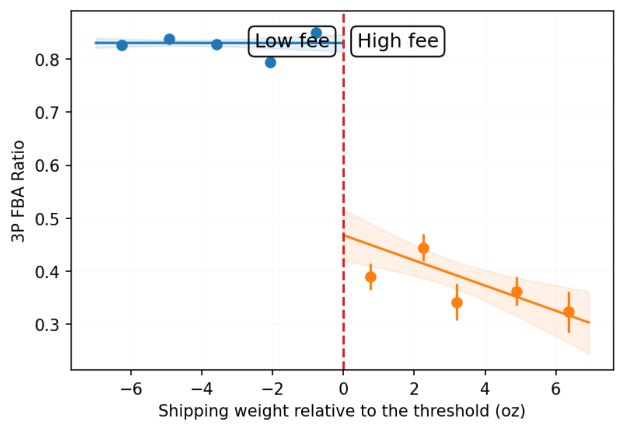
(b) Large to Bulky

Notes. This figure shows the heatmaps of density estimates around size-tier cutoffs defined by product size and shipping weight. Panels (a) and (b) display the distributions around the cutoffs from the small standard tier to the large standard tier and from the large standard tier to the large bulky tier, respectively. In each panel, the black dashed lines indicate cutoffs based on either product size measures ($d_j^{\text{size,tier}}$) or shipping weight measures ($d_j^{\text{shwgt,tier}}$). Each cell reports the average kernel density estimates for products in the corresponding size–weight bin, averaged over time as well. The total number of products in panels (a) and (b) is 1,620 and 3,356, respectively.

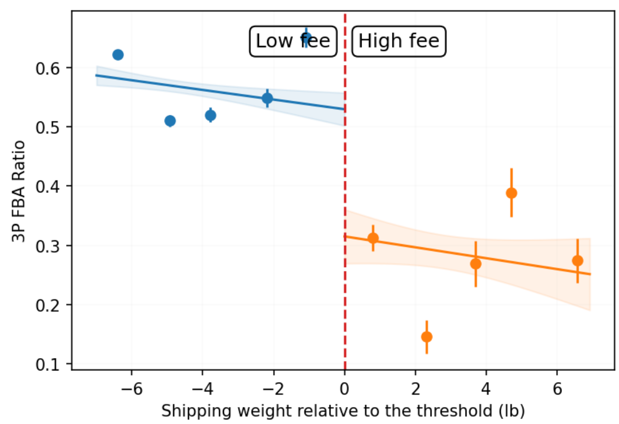
Figure A4: Results on FBA Seller Ratio in Other Cutoffs



(a) Small to Large (dim)



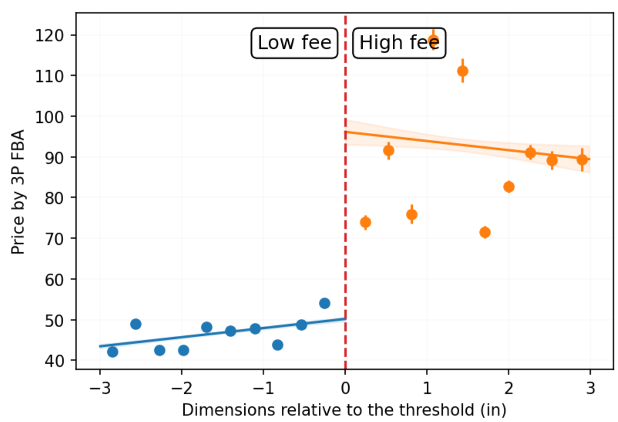
(b) Small to Large (shwgt)



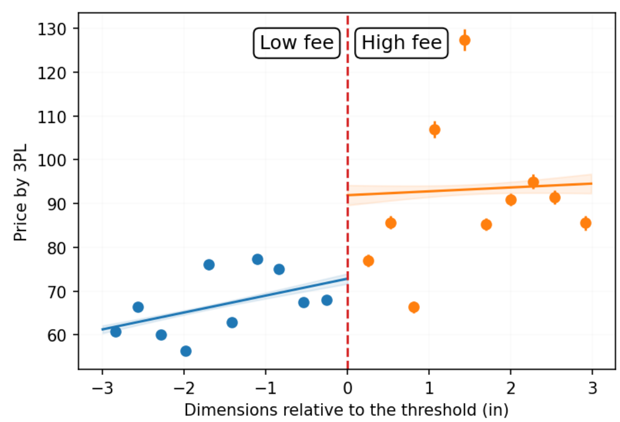
(c) Large to Bulky (shwgt)

Notes. This figure presents the regression discontinuity estimates of independent seller ratios from (2) around the three cutoffs. Dots are averages of the outcome within bins of the running variable, and the solid lines are local-linear fits estimated separately on each side of the cutoff with MSE-optimal bandwidths (Calonico *et al.*, 2014); shaded regions denote 95% confidence intervals. Panel (a), (b) and (c) plot the results of small to large with product size, small to large with shipping weight size, and large to bulky with shipping weight size, respectively.

Figure A5: Prices by Logistics Choice



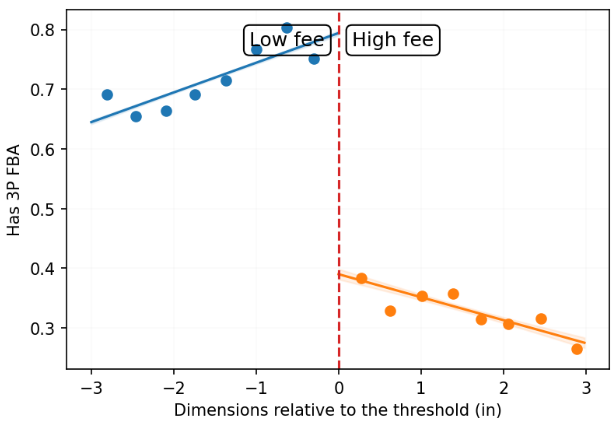
(a) Price by FBA Seller



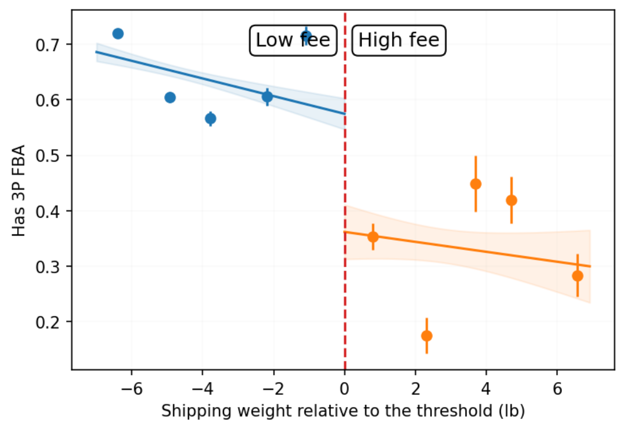
(b) Price by 3PL Seller

Notes. This figure presents the regression discontinuity estimates from (2) around the large size-tier cutoff, using the product-size running variable. In each panel, the horizontal axis is the normalized distance to the cutoff: positive values correspond to products in the larger size tier, which are charged higher FBA fulfillment fees, and negative values correspond to products in the smaller tier. Dots are averages of the outcome within bins of the running variable, and the solid lines are local-linear fits estimated separately on each side of the cutoff with MSE-optimal bandwidths (Calonico *et al.*, 2014); shaded regions denote 95% confidence intervals. Panel (a) and (b) plot the consumer prices by sellers using FBA and independent logsitics, respectively.

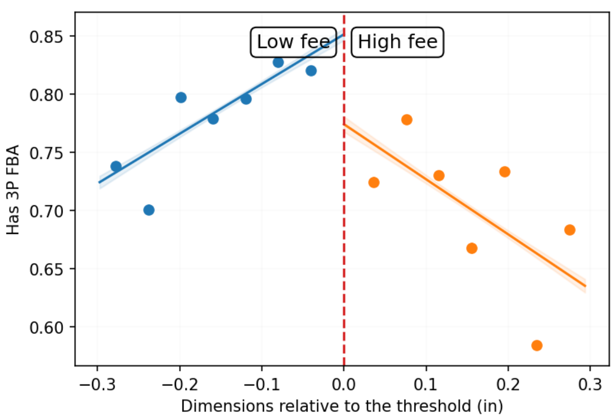
Figure A6: Has Independent FBA Seller



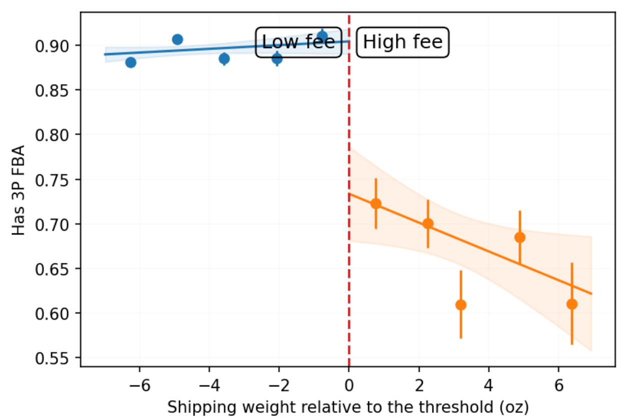
(a) Large to Bulky (dim)



(b) Large to Bulky (shwgt)



(c) Small to Large (dim)



(d) Small to Large (shwgt)

Notes. This figure presents the regression discontinuity estimates of having an independent seller for each product from (2) around every cutoff in A3. Dots are averages of the outcome within bins of the running variable, and the solid lines are local-linear fits estimated separately on each side of the cutoff with MSE-optimal bandwidths (Calonico *et al.*, 2014); shaded regions denote 95% confidence intervals. Panel (a), (b), (c), and (d) plot the results of small to large with product size size, small to large with shipping weight size, large to bulky with shipping weight size, and large to bulky with product size size, respectively.

D More on Consumer Demand

D.1 Deriving and Computing Market Shares

Let δ_{jft} denote the mean utility and μ_{ijft} collect the consumer-specific deviations from mean utility generated by the demographic interactions and random coefficients. Then, we can rewrite the utility model in (3) as

$$U_{ijft} = \delta_{jft} + \mu_{ijft} + \bar{\epsilon}_{ift} + (1-\rho)\bar{\epsilon}_{ijft}. \tag{D.25}$$

Define the inclusive value of platform f for consumer i,

$$IV_{ift} = (1-\rho)\log \sum_{k\in\mathcal{J}_{ft}} \exp\left(\frac{\delta_{kft} + \mu_{ikft}}{1-\rho}\right),$$

where $\mathcal{J}_{ft}$ is the set of products offered on platform f in month t. Given the nested-logit error structure, the probability that consumer i chooses product j on platform f decomposes into the within-platform conditional probability and the probability of selecting platform f:

$$\text{sh}_{ijft} = \text{sh}_{ijft|f} \cdot \text{sh}_{ift} = \frac{\exp\big[(\delta_{jft} + \mu_{ijft})/(1-\rho)\big]}{\exp\big[IV_{ift}/(1-\rho)\big]} \cdot \frac{\exp IV_{ift}}{1 + \sum_{f'\in\mathcal{F}} \exp IV_{if't}}. \tag{D.26}$$

The one in the denominator is the inclusive value of the outside option, which is normalized to zero ($\delta_{0t} = \mu_{i0t} = 0$).

I use the Halton sequence method (Halton, 1960) to simulate the random draws, ν, from the standard normal density. This improves the coverage of the integration domain relative to pseudo-random Monte Carlo, yielding a faster convergence rate of $O(R^{-1}(\log R))$ rather than $O(R^{-1/2})$ where R is the number of draws (Train, 2009). The integration with respect to the normal density in the market share function (8) is approximated as

$$\text{sh}_{jft} \;\approx\; \sum_{\tau\in\mathcal{T}} w_{\tau t} \cdot \frac{1}{R}\sum_{r=1}^{R} \text{sh}_{ijft}(\tau, u_r), \tag{D.27}$$

where $u_r = \Phi^{-1}(\eta_r)$ and $\{\eta_r\}_{r=1}^{R} \subset [0,1]$ is a 1-sizeal Halton sequence with coprime prime base. I set $R = 100$.

D.2 Defining Market Size

The market size is defined as the number of households that purchased any kitchen appliance across all subcategories, N_t^H, times the Google Trends search interest for the subcategory, $\text{GoogleTrends}_{ct} \in [0,1]$. That is,

$$M_{ct} = N_t^H \times \text{GoogleTrends}_{ct} \tag{D.28}$$

To compute N_t^H, I project the number of purchasing households in the Numerator dataset for a given month t to represent the total U.S. household population using demographic weights (“DEMO_WEIGHTS”) and national factors (“NATIONAL_FACTOR”).

To construct $\text{GoogleTrends}_{c(j)t}$, I first obtain daily search popularity data from the Google Trends for each subcategory keyword (e.g., air fryers) and aggregate them into monthly averages.

D.3 Micro Moments

Following Petrin (2002), I match each micro moment with its model-predicted counterpart. The sample analogues are constructed from the Numerator consumer panel. Let N_t^H be the number of households who purchased any kitchen appliance in month t, let $y_{ijft} \in \{0,1\}$ indicate that household i purchases product j on platform f in month t, and let $\mathcal{J}_{ft}$ denote the set of products available on platform f at time t. For example, the sample analogue of the average log price paid by households in income group g is

$$\hat{\mathbb{E}}[\log p_{jft} \,|\, \text{Inc}_g = 1] = \frac{\sum_t \sum_{i=1}^{N_t^H} \sum_f \sum_{j \in \mathcal{J}_{ft}} y_{ijft} \log p_{jft} \cdot \mathbf{1}\{\text{Inc}_{g,it} = 1\}}{\sum_t \sum_{i=1}^{N_t^H} \mathbf{1}\{\text{Inc}_{g,it} = 1\}}.$$

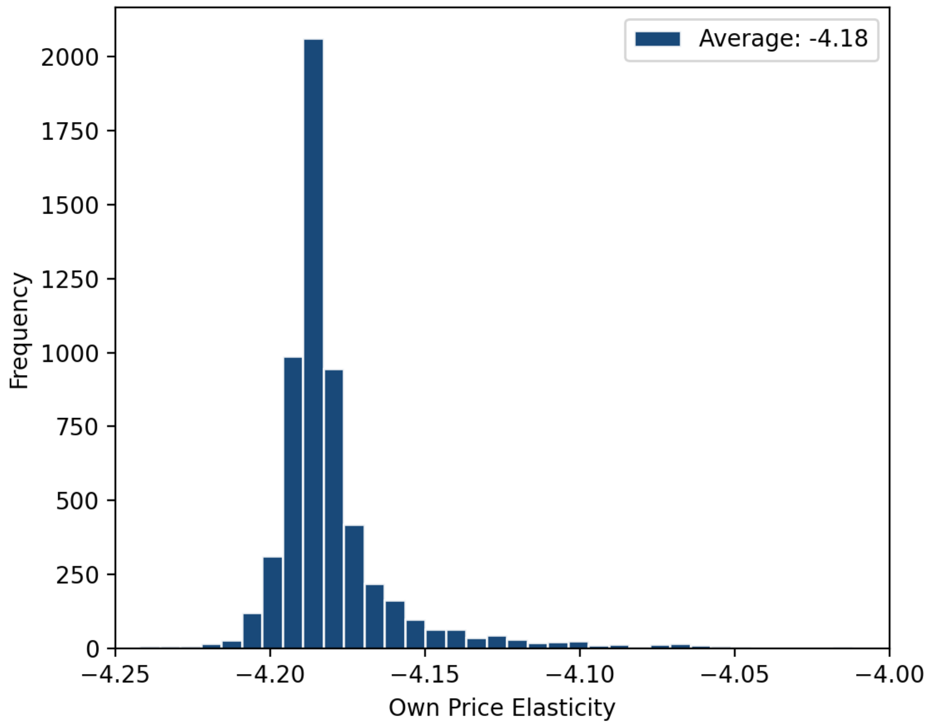
The remaining moments—average log price conditional on Prime and Walmart+ subscription status, platform choice probabilities conditional on subscription status, and the unconditional second moment of log price—are constructed analogously.

The model-implied counterparts replace observed purchases with predicted choice probabilities. Let I_t denote the set of simulated consumer types in month t, w_{it} the integration weight for type i, and $s_{ijft}(\boldsymbol{\theta})$ the model-predicted probability that type i purchases product j on platform f in month t. The counterpart to the moment above is

$$\mathbb{E}[\log p_{jft} \,|\, \text{Inc}_g = 1] = \frac{\sum_t \sum_{i \in I_t} w_{it} \sum_f \sum_{j \in \mathcal{J}_{ft}} s_{ijft}(\boldsymbol{\theta}) \log p_{jft} \cdot \mathbf{1}\{\text{Inc}_{g,it} = 1\}}{\sum_t \sum_{i \in I_t} w_{it} \sum_f \sum_{j \in \mathcal{J}_{ft}} s_{ijft}(\boldsymbol{\theta}) \cdot \mathbf{1}\{\text{Inc}_{g,it} = 1\}},$$

with the other model-predicted moments constructed in the same manner. I implement these micro moments using the framework of Conlon and Gortmaker (2025), to which I refer the reader for the general construction.

Figure A7: Distribution of Own Price Elasticity



Notes. This figure shows the distribution of own price elasticity from estimating the demand model of (3).

E More on Variable and Marginal Costs

E.1 Recovering Variable Cost from Marginal Cost Function

Suppose the marginal cost function has the following form

$$MC(Q) = C_0 + h_0(Q) \tag{E.29}$$

By the definition of the variable and marginal cost,

$$VC(Q) = \int_0^Q MC(q)\ \mathrm{d}q = \int_0^Q (C_0 + h_0(q))\,\mathrm{d}q = C_0 Q + \int_0^Q h_0(q)\ \mathrm{d}q$$

Therefore, the average variable cost is

$$AVC(Q) = \frac{AVC(Q)}{Q} = C_0 + \frac{\int_0^Q h_0(\bar{Q})\ \mathrm{d}q}{Q}$$

If the marginal cost function is linear in Q (i.e., $h_0(Q) \equiv \beta_0 Q$), $AVC(Q)$ is also the linear function of Q as:

$$AVC(Q) = C_0 + \frac{\int_0^Q \beta_0 q \ \mathrm{d}q}{Q} = C_0 + \frac{\beta_0}{2} Q$$

This means that the sign of β_0 determines also the sign of the economies of scale in variable costs.

Suppose the marginal cost function is linear in $\log(Q)$ (i.e., $h_0(Q) \equiv \gamma_0 \log(Q)$). The variable cost is then

$$VC(Q) = \int_0^Q MC(q) \ \mathrm{d}q = \int_0^Q \big(C_0 + \gamma_0 \log q\big) \, \mathrm{d}q = C_0 Q + \gamma_0 \int_0^Q \log q \ \mathrm{d}q.$$

By the integration by parts:

$$\int_0^Q \log q \ \mathrm{d}q = \Big[q \log q\Big]_0^Q - \int_0^Q q \cdot \tfrac{1}{q} \ \mathrm{d}q = Q \log Q - Q.$$

Therefore,

$$VC(Q) = C_0 Q + \gamma_0 Q(\log Q - 1) = (C_0 - \gamma_0)Q + \gamma_0 Q \log Q,$$

and dividing by Q yields the average variable cost

$$AVC(Q) = \frac{VC(Q)}{Q} = (C_0 - \gamma_0) + \gamma_0 \log Q.$$

The functional form of AVC is therefore identical to that of MC with the same slope coefficient γ_0.

F Simulation Details

F.1 Pricing Simulations with Endogenous Marginal Costs

Rewrite the seller's first-order conditions in (12):

$$\mathbf{p} \;=\; \widetilde{\mathbf{mc}}(\bar{\mathbf{Q}}(p)) \;-\; \big(\mathbf{p}\big)^{-1}\mathbf{sh}\big(\mathbf{p}\big), \tag{F.30}$$

where is $J \times J$ matrix whose (j,k) element is $1\{j \in \mathcal{J}_s\} \times 1\{k \in \mathcal{J}_s\} \times (-\partial \mathrm{sh}_j / \partial p_k)$. $\mathbf{sh}_s$ stacks the corresponding market shares. $\widetilde{\mathbf{mc}}(\bar{\mathbf{Q}}(p))$ is an equilibrium object.

I use the equation (F.30) to conduct the fixed-point iteration to find counterfactual equilibrium prices. To be specific, suppose $\mathbf{p}^{(n)}$ be the prices at iteration n. Then, I update the prices to attain $\mathbf{p}^{(n+1)}$ according to the following rule: $\lambda \in (0,1]$:

$$\mathbf{p}^{(n+1)} \;=\; (1-\lambda)\,\mathbf{p}^{(n)} \;+\; \lambda\Big[\widetilde{\mathbf{mc}}\big(\mathbf{p}^{(n)}\big) - \big(\mathbf{p}^{(n)}\big)^{-1}\mathbf{sh}\big(\mathbf{p}^{(n)}\big)\Big]\,.$$

Algorithm A1 makes the order of operations explicit; I run the algorithm jointly across all sellers' products in each market. I initialize at observed prices, $\mathbf{p}^{(0)} = \mathbf{p}^{\mathrm{obs}}$, and use $\lambda = 0.5$.

Algorithm A1 Fixed-point iteration for equilibrium prices with economies of scale

Require: market size vector $\mathbf{M}$; functions $\mathbf{sh}(\cdot)$, $\tilde{\mathbf{mc}}(\cdot)$ and $\Omega(\cdot)$; initial $\boldsymbol{p}^{(0)}$; step $\lambda \in (0,1]$; tol > 0; max_iter.

$n \leftarrow 0,\; \Delta \leftarrow \infty$
while $\Delta >$ tol **and** $n <$ max_iter **do**
    $\mathbf{sh}^{(n)} \leftarrow \mathbf{sh}\big(\mathbf{p}^{(n)}\big)$
    $\mathbf{Q}^{(n)} \leftarrow \mathbf{M}\mathbf{sh}^{(n)}$
    $\tilde{\mathbf{mc}}^{(n)} \leftarrow \tilde{\mathbf{mc}}(\bar{\mathbf{Q}}^{(n)})$
    $\boldsymbol{\Omega}^{(n)} \leftarrow \boldsymbol{\Omega}\big(\boldsymbol{p}^{(n)}\big)$
    $\widehat{\mathbf{p}} \leftarrow \tilde{\mathbf{mc}}^{(n)} + \big(\boldsymbol{\Omega}^{(n)}\big)^{-1}\mathbf{sh}^{(n)}$
    $\mathbf{p}^{(n+1)} \leftarrow (1-\lambda)\,\mathbf{p}^{(n)} + \lambda\,\widehat{\mathbf{p}}$
    $\Delta \leftarrow \big\|\mathbf{p}^{(n+1)} - \mathbf{p}^{(n)}\big\|_{\infty}; \quad n \leftarrow n+1$
end while
return $\mathbf{p}^{(n+1)}$

G More on Entry and Logistics Choices with Fixed Cost

Table A4: Entry and Logistics Choice Set of Seller s

$\mathbf{d}_s$			
e_{sAmz}	e_{sWmt}	ℓ_{sAmz}	ℓ_{sWmt}
1	1	1	1
1	1	1	0
1	1	0	1
1	1	0	0
1	0	1	0
1	0	0	0
0	1	0	1
0	1	0	0

Notes. This table shows the discrete decisions that a seller can take at the first entry and logistics choice stage.

G.1 Identification Detail

Suppose a seller s chooses $\mathbf{d}_s^* \in \mathcal{D}$ as an optimal decision as in (15). Holding others' decision fixed as $\mathbf{d}_{-s}$, the revealed preference rationale with the decision rule in (15) implies that for any deviation $\mathbf{d}_s' \neq \mathbf{d}_s^*$,

$$\begin{aligned} &\mathbb{E}_{(\xi,\omega)}\left[\Pi_s(\mathbf{d}_s^*, \mathbf{d}_{-s})\right] \geq \mathbb{E}_{(\xi,\omega)}\left[\Pi_s(\mathbf{d}_s', \mathbf{d}_{-s})\right] \\ \Leftrightarrow\ &\mathbb{E}_{(\xi,\omega)}\left[\pi_s(\mathbf{d}_s^*, \mathbf{d}_{-s}))\right] - \bar{FC}_s(\mathbf{d}_s^*) - \nu_s(\mathbf{d}_s^*) \geq \mathbb{E}_{(\xi,\omega)}\left[\pi_s(\mathbf{d}_s', \mathbf{d}_{-s}))\right] - \bar{FC}_s(\mathbf{d}_s') - \nu_s(\mathbf{d}_s') \end{aligned} \tag{G.31}$$

where $\bar{FC}_s(\mathbf{d}) = \sum_{j\in\mathcal{J}_s} \bar{FC}(\mathbf{d}) \equiv |\mathcal{J}_s|\bar{FC}(\mathbf{d})$ and $\nu_s(\mathbf{d}) = \sum_{j\in\mathcal{J}_s} \nu_j(\mathbf{d})$ for any $\mathbf{d} \in \mathcal{D}$. $|\mathcal{J}_s|$ means the number of products in the set $\mathcal{J}_s$.

For any pair $(\mathbf{d}, \mathbf{d}') \in \mathcal{D} \times \mathcal{D}$, denote $\Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}') \equiv \mathbb{E}_{(\xi,\omega)}\left[\pi_s(\mathbf{d}, \mathbf{d}_{-s}))\right] - \mathbb{E}_{(\xi,\omega)}\left[\pi_s(\mathbf{d}', \mathbf{d}_{-s}))\right]$ and $FC_s(\mathbf{d}) - FC_s(\mathbf{d}') \equiv \Delta FC_s(\mathbf{d}, \mathbf{d}') = \Delta\bar{FC}_s(\mathbf{d}, \mathbf{d}') + \Delta\nu_s(\mathbf{d}, \mathbf{d}')$. We can attain the first base inequality condition for identifying fixed costs by rearranging the terms in (G.31) as:

$$\Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}') \geq \Delta\bar{FC}_s(\mathbf{d}, \mathbf{d}') + \Delta\nu_s(\mathbf{d}, \mathbf{d}') \qquad \text{for } \mathbf{d} = \mathbf{d}_s^* \text{ and } \mathbf{d}' \neq \mathbf{d}_s^* \tag{G.32}$$

This inequality means that the differences between the expected variable profits from the observed optimal choice d_s^* and any deviation d_s' is larger than incurred fixed cost differences of them. We can similarly formulate the second base inequality by using the flip side:

$$\Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}') \leq \Delta\bar{FC}_s(\mathbf{d}, \mathbf{d}') + \Delta\nu_s(\mathbf{d}, \mathbf{d}') \qquad \text{for } \mathbf{d} \neq \mathbf{d}_s^* \text{ and } \mathbf{d}' = \mathbf{d}_s^* \tag{G.33}$$

which comes from the decision rule that every non-optimal decision is weakly dominated by the optimal decision.

Although these inequalities (G.32) and (G.33) are highly informative as an upper and lower bound of $\Delta\bar{FC}_s(\mathbf{d}, \mathbf{d}')$, the *selection bias* hinders us from directly using the above inequality conditions. Specifically, there can be bias from the fact that *conditional* expectation of differences of structural error term is different from *unconditional* expectation of them as $\mathbb{E}\left[\Delta\nu_s(\mathbf{d}, \mathbf{d}')|d = d^*\right] \neq \mathbb{E}\left[\Delta\nu_s(\mathbf{d}, \mathbf{d}')\right] = 0$ and $\mathbb{E}\left[\Delta\nu_s(\mathbf{d}, \mathbf{d}')|d \neq d^*\right] \neq \mathbb{E}\left[\Delta\nu_s(\mathbf{d}, \mathbf{d}')\right] = 0$. Notably, given that we have identified demand and marginal cost functions, which in turn allows us to treat expected variable profits as observed quantities, this selection bias is the only remaining identification challenge. To circumvent this, we need an additional assumption to take unconditional expectations on the structural error terms.

I follow the approach by Eizenberg (2014) and assume that the support of differences in fixed costs fall within the range of the supremum and infimum of expected variable profit differences:

$$\Delta FC_s(\mathbf{d}, \mathbf{d}') \subset \left[\inf_s \Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}'), \sup_s \Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}')\right] \text{ for any } s \in \mathcal{S} \tag{G.34}$$

With this assumption, I can define the following lower and upper bounds: for any choice $\mathbf{d} \in \mathcal{D}$ and its deviation $\mathbf{d}' \in \mathcal{D} \setminus \{\mathbf{d}\}$,

$$\Delta FC_s^L = \begin{cases} \Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}') & \text{if } \mathbf{d} \neq \mathbf{d}_s^* \\ \inf_s \Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}') & \text{if } \mathbf{d} = \mathbf{d}_s^* \end{cases} \qquad \Delta FC_s^U = \begin{cases} \Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}') & \text{if } \mathbf{d} = \mathbf{d}_s^* \\ \sup_s \Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}') & \text{if } \mathbf{d} \neq \mathbf{d}_s^* \end{cases} \tag{G.35}$$

This support restriction allows me to construct following inequality for any d and d' as

$$\Delta FC_s^L(\mathbf{d}, \mathbf{d}') \leq \Delta FC_s(\mathbf{d}, \mathbf{d}') \leq \Delta FC_s^U(\mathbf{d}, \mathbf{d}') \tag{G.36}$$

As this inequality holds for every seller s, we can take *unconditional* expectations:

$$\mathbb{E}\left[\Delta FC_s^L(\mathbf{d}, \mathbf{d}')\right] \leq \Delta\overline{FC}_s(\mathbf{d}, \mathbf{d}') \leq \mathbb{E}\left[\Delta FC_s^U(\mathbf{d}, \mathbf{d}')\right] \tag{G.37}$$

where $\Delta\overline{FC}_s(\mathbf{d}, \mathbf{d}') = \mathbb{E}\left[\Delta FC_s(\mathbf{d}, \mathbf{d}')\right] = \mathbb{E}\left[\Delta\overline{FC}_s(\mathbf{d}, \mathbf{d}') + \Delta\nu_s(\mathbf{d}, \mathbf{d}')\right]$. I can use this inequality (G.37) with unconditional expectation to construct a moment inequality estimator for the fixed cost parameters.

G.1.1 Estimation of the Fixed Costs

Sample analogue I form the sample analogue of (G.37) at the product-month level. I first compute the profit difference $\Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}')$ for every pair of $(\mathbf{d}, \mathbf{d}') \in \mathcal{D}$, holding other's decision vectors fixed at the observed choice. According to (G.35), I compute the ΔFC_s^L and ΔFC_s^U by taking minimum and maximum among computed $\Delta\bar{\pi}_s(\mathbf{d}, \mathbf{d}')$. This allows me to compute the sample analogue version of (G.37) for all $s \in \mathcal{S}^{3\text{P}}$ as:

$$\begin{aligned} \Delta\overline{FC}_s^L(\mathbf{d}, \mathbf{d}') \ &\leq \ \overline{FC}_s(\mathbf{d}, \boldsymbol{\theta}) - \overline{FC}_s(\mathbf{d}', \boldsymbol{\theta}) \ \leq \ \Delta\overline{FC}_s^U(\mathbf{d}, \mathbf{d}') && \Leftrightarrow \\ \Delta\overline{FC}_s^L(\mathbf{d}, \mathbf{d}') \ &\leq \ |\mathcal{J}_s|\left(\overline{FC}(\mathbf{d}, \boldsymbol{\theta}) - \overline{FC}(\mathbf{d}', \boldsymbol{\theta})\right) \ \leq \ \Delta\overline{FC}_s^U(\mathbf{d}, \mathbf{d}') && \Leftrightarrow \\ \frac{\Delta\overline{FC}_s^L(\mathbf{d}, \mathbf{d}')}{|\mathcal{J}_s|} \ &\leq \ \overline{FC}(\mathbf{d}, \boldsymbol{\theta}) - \overline{FC}(\mathbf{d}', \boldsymbol{\theta}) \ \leq \ \frac{\Delta\overline{FC}_s^U(\mathbf{d}, \mathbf{d}')}{|\mathcal{J}_s|} \end{aligned} \tag{G.38}$$

Therefore, for each $(\mathbf{d}, \mathbf{d}')$, I can take average of lower and upper bounds of (G.38) and define

$$\Delta\overline{FC}^{L}_{(\mathbf{d},\mathbf{d}')} \equiv \frac{1}{N_{(\mathbf{d},\mathbf{d}')}} \sum_{s\in\{s|\mathbf{d}^*_s\in\{\mathbf{d},\mathbf{d}'\}\}} \frac{\Delta\overline{FC}^{L}_{s}(\mathbf{d},\mathbf{d}')}{|\mathcal{J}_s|}$$

$$\Delta\overline{FC}^{U}_{(\mathbf{d},\mathbf{d}')} \equiv \frac{1}{N_{(\mathbf{d},\mathbf{d}')}} \sum_{s\in\{s|\mathbf{d}^*_s\in\{\mathbf{d},\mathbf{d}'\}\}} \frac{\Delta\overline{FC}^{U}_{s}(\mathbf{d},\mathbf{d}')}{|\mathcal{J}_s|}$$

where $N_{(\mathbf{d},\mathbf{d}')}$ denotes the effective sample size that excludes sellers whose observed choices are neither $\mathbf{d}$ nor $\mathbf{d}'$.

Linearizing in $\boldsymbol{\theta}$ Under the parametric specification (**??**), the fixed-cost difference in (G.38) is linear in $\boldsymbol{\theta}$:

$$\overline{FC}(\mathbf{d},\boldsymbol{\theta}) - \overline{FC}(\mathbf{d}',\boldsymbol{\theta}) \;=\; \big(a(\mathbf{d}) - a(\mathbf{d}')\big)^{\intercal}\boldsymbol{\theta} \;\equiv\; a^{\intercal}_{(\mathbf{d},\mathbf{d}')}\boldsymbol{\theta}$$

where $a(\mathbf{d}) = (e_{\text{Amz}},\, e_{\text{Wmt}},\, e_{\text{Amz}}\,\ell_{\text{Amz}},\, e_{\text{Wmt}}\,\ell_{\text{Wmt}},\, e_{\text{Amz}}\,\ell_{\text{Wmt}},\, e_{\text{Wmt}}\,\ell_{\text{Amz}})$ is the six-sizeal design vector mapping the decision $\mathbf{d} = (e_{\text{Amz}}, e_{\text{Wmt}}, \ell_{\text{Amz}}, \ell_{\text{Wmt}})$ into the regressor space of (**??**), and $\boldsymbol{\theta} \in \mathbb{R}^6$ collects the corresponding fixed-cost parameters. Each retained pair therefore contributes two linear inequalities in $\boldsymbol{\theta}$:

$$\Delta\overline{FC}^{L}_{(\mathbf{d},\mathbf{d}')} \;\le\; a^{\intercal}_{(\mathbf{d},\mathbf{d}')}\boldsymbol{\theta} \;\le\; \Delta\overline{FC}^{U}_{(\mathbf{d},\mathbf{d}')}. \tag{G.39}$$

Stacking the C retained pairs and writing $A\boldsymbol{\theta} \le b$ for the resulting $2C$ one-sided constraints, the sample identified set is $\{\boldsymbol{\theta} : A\boldsymbol{\theta} \le b\}$ whenever this set is non-empty.

Linear programming The fixed-cost parameter is set-identified by the linear moment inequalities $A\boldsymbol{\theta} \le b$, the stacked system of $2C$ cell-level bounds, so I summarize each scalar functional by its projection onto the feasible region. Let $\Theta_I = \{\boldsymbol{\theta} \in \mathbb{R}^6 : A\boldsymbol{\theta} \le b\}$ denote the (sample) identified set. For a parameter coordinate θ_k—or any linear functional $a(\mathbf{d})'\boldsymbol{\theta}$, such as a fixed cost $FC(\mathbf{d})$—the projected identified set $[\hat{\theta}^L_k, \hat{\theta}^U_k]$ is the pair of linear programs

$$\hat{\theta}^L_k = \min_{\boldsymbol{\theta}\in\Theta_I} e'_k\boldsymbol{\theta}, \qquad \hat{\theta}^U_k = \max_{\boldsymbol{\theta}\in\Theta_I} e'_k\boldsymbol{\theta}, \tag{G.40}$$

where e_k is the k-th unit vector.

Because the system is over-identified and may be empty in finite samples due to simulation noise, I do not impose $A\boldsymbol{\theta} \le b$ exactly but relax it by the minimum amount needed for feasibility. In a first stage I solve the single linear program

$$\delta^* = \min_{\boldsymbol{\theta}\in\mathbb{R}^6,\,\mathbf{s}\ge 0} \mathbf{1}'\mathbf{s} \quad \text{s.t.} \quad A\boldsymbol{\theta} - \mathbf{s} \le b, \tag{G.41}$$

where $\mathbf{s} = (s_1, \ldots, s_{2C})' \ge 0$ are non-negative slacks; δ^* is the smallest total inequality violation achievable under the parametric form, and $\delta^* = 0$ if and only if $\Theta_I \neq \varnothing$. In a second stage I project each functional over the minimum-slack polytope

$$\Theta^*_I = \big\{(\boldsymbol{\theta}, \mathbf{s}) : A\boldsymbol{\theta} - \mathbf{s} \le b,\ \mathbf{s} \ge 0,\ \mathbf{1}'\mathbf{s} \le (1+\epsilon)\,\delta^*\big\},$$

i.e. I replace Θ_I by Θ^*_I in (G.40). When the inequalities are sample-feasible, $\delta^* = 0$ and $\Theta^*_I = \Theta_I$, so (G.40) returns the exact projection of the identified set; otherwise it returns the projection of the least-violating set.

H Fee Schedules of Amazon and Independent Logistics

This section documents the empirical pattern about fee schedules of Amazon and Independent logistics.

H.1 Data

I digitize the posted fee schedules of the three fee-setters for the years $t \in \{2022, 2023, 2024, 2025\}$ and evaluate them on a common grid. The unit of observation is a parcel weight class $j \in \{1, \ldots, 20\}$ lb in year t. Each cell records Amazon's non-peak fulfillment fee $\text{fee}^{\ell}_{jt\text{Amz}}$ and the UPS and FedEx Ground rates $\text{fee}^{\text{UPS}}_{jt}$ and $\text{fee}^{\text{FedEx}}_{jt}$, evaluated at zone 5 for a parcel.

H.2 Correlations of Fee Changes

For parcel j and logistics provider $k \in \{\text{Amz}, \text{UPS}, \text{FedEx}\}$, let the cumulative rate change over the window be

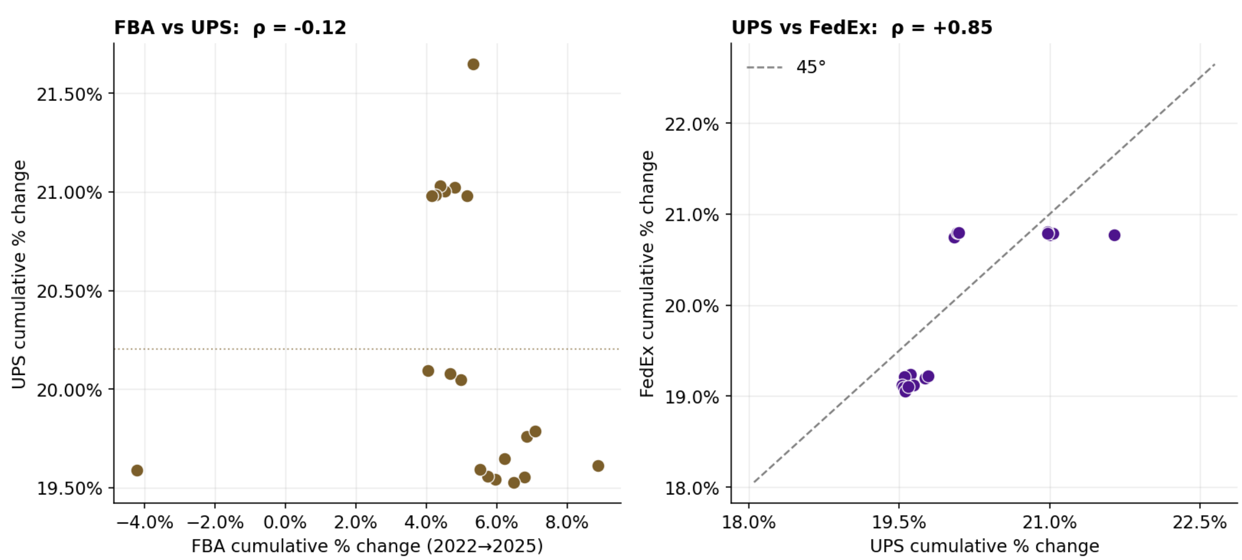
$$g^k_j \;=\; 100\left(\frac{\text{fee}^k_{j,2025}}{\text{fee}^k_{j,2022}} - 1\right), \qquad \text{fee}^{\text{Amz}}_{jt} \equiv \text{fee}^{\ell}_{jt\text{Amz}}. \tag{H.42}$$

Because g is a cumulative growth rate, correlating it across parcels nets out both price *levels* and any common *trend*, isolating whether a carrier raised rates most in the same parcel segments where Amazon did. The Pearson correlations are

$$\rho\Big(g^{\text{Amz}}, g^{\text{UPS}}\Big) = -0.12, \qquad \rho\Big(g^{\text{Amz}}, g^{\text{FedEx}}\Big) = -0.19, \qquad \rho\Big(g^{\text{UPS}}, g^{\text{FedEx}}\Big) = +0.85.$$

Amazon's per-parcel changes are essentially uncorrelated with either carrier's, while the two carriers are almost perfectly correlated with each other (Figure A8). The carriers co-move with one another, not with Amazon.

Figure A8: Correlations of Fee Changes



Notes. Each point is one parcel weight class. The left panel shows Amazon versus UPS ($\rho = -0.12$) and the right panel shows UPS versus FedEx ($\rho = +0.85$).

H.3 Panel Regressions

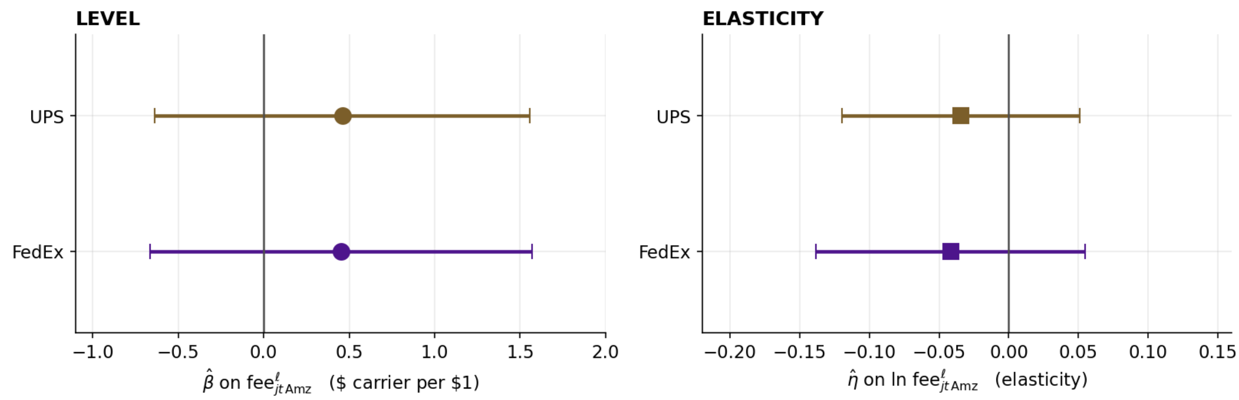
I formalize the pattern with a short panel in which weight class j is the entity and year t the time index. Writing fee^k_{jt} for the carrier rate, I estimate, for $k \in \{\text{UPS}, \text{FedEx}\}$, the two-way fixed effects specifications

$$\text{fee}^k_{jt} = \alpha_j + \gamma_t + \beta\,\text{fee}^\ell_{jt\text{Amz}} + \varepsilon_{jt}, \tag{H.43}$$

$$\log(\text{fee}^k_{jt}) = \alpha_j + \gamma_t + \eta\,\log(\text{fee}^\ell_{jt\text{Amz}}) + u_{jt}, \tag{H.44}$$

where the weight effects α_j and γ_t absorb the common weight and year-specific changes.

Figure A9: Two-Way Fixed Effects Regression Results

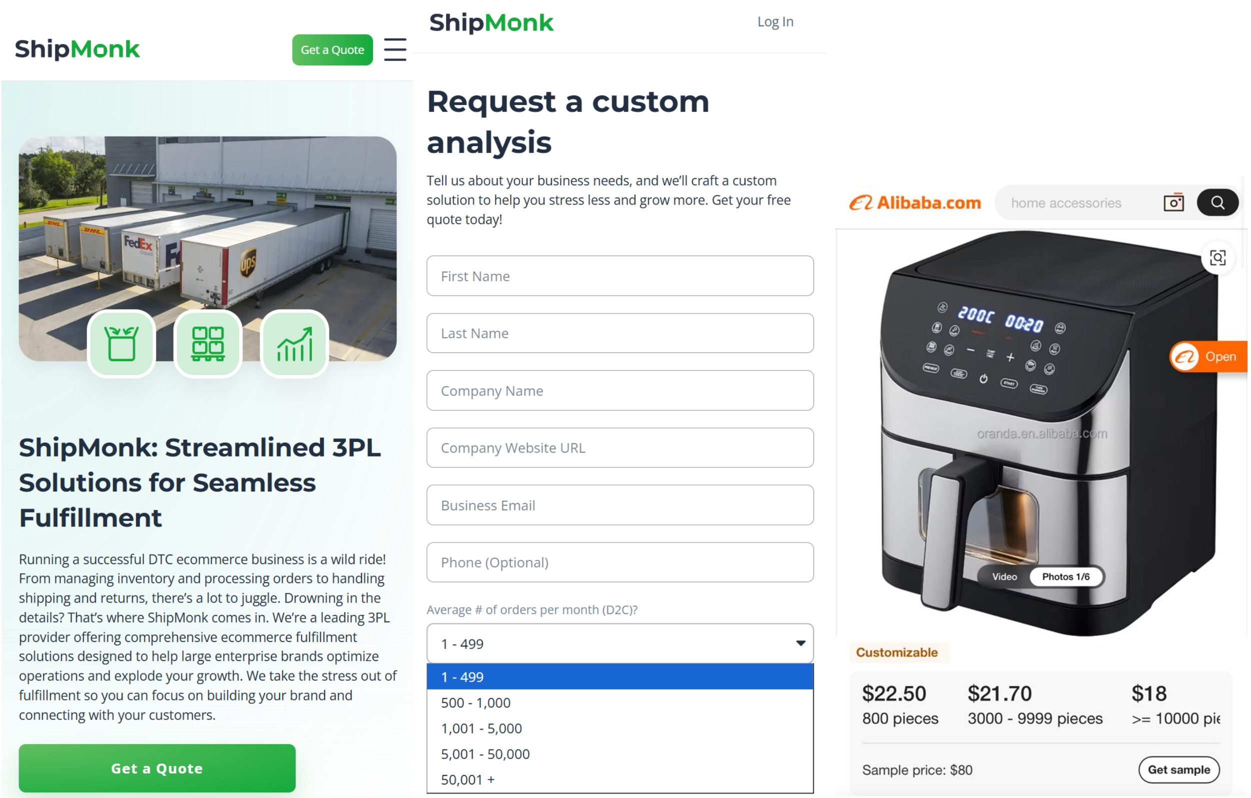


Notes. These figures show two-way fixed-effects estimates of the Amazon-fee coefficient, in level ($\hat{\beta}$, left) and elasticity ($\hat{\eta}$, right), with 95% confidence intervals clustered by weight class.

The estimates appear in Figure A9. In the level specification $\hat{\beta} = 0.46$ (s.e. $= 0.56$) and in the elasticity specification $\hat{\eta} = -0.03$ (s.e. $= 0.04$); neither is statistically distinguishable from zero, for either carrier.

I Additional Figures and Tables

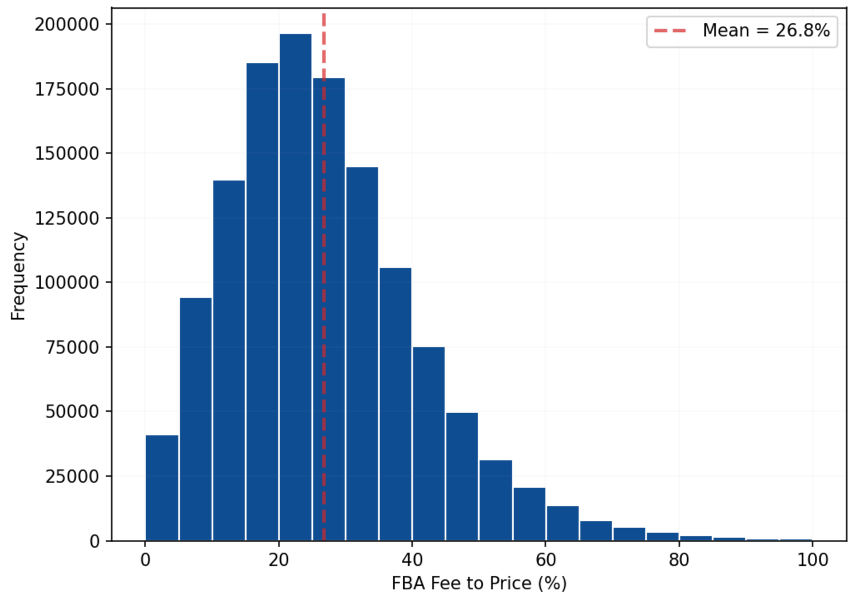
Figure A10: Evidence for Scale Economies in Seller Variable Costs



(a) 3PL Service Provider (ShipMonk) (b) Quantity-Based 3PL Fee Quote (c) Quantity Discounts in Wholesaling

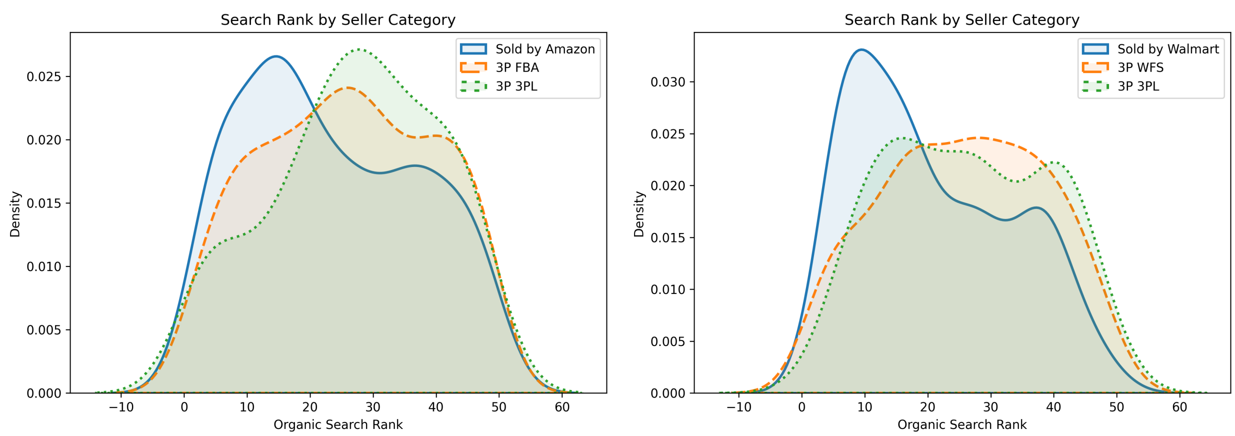
Notes. These figures show the examples of quantity discount on e-commerce logistics and wholesaling, supporting the role of economies of scale in the cost-side.

Figure A11: Distribution of FBA Fee to Price



Notes. This figures shows the distribution of proportions that FBA fee takes with respect to consumer prices. The sample includes only product-seller pair at monthly level, conditioning on using FBA. FBA fees take a significant portion, on average 26.8%, of overall prices.

Figure A12: Distribution of Organic Search Ranks by Seller Category and Platform



(a) Amazon (b) Walmart

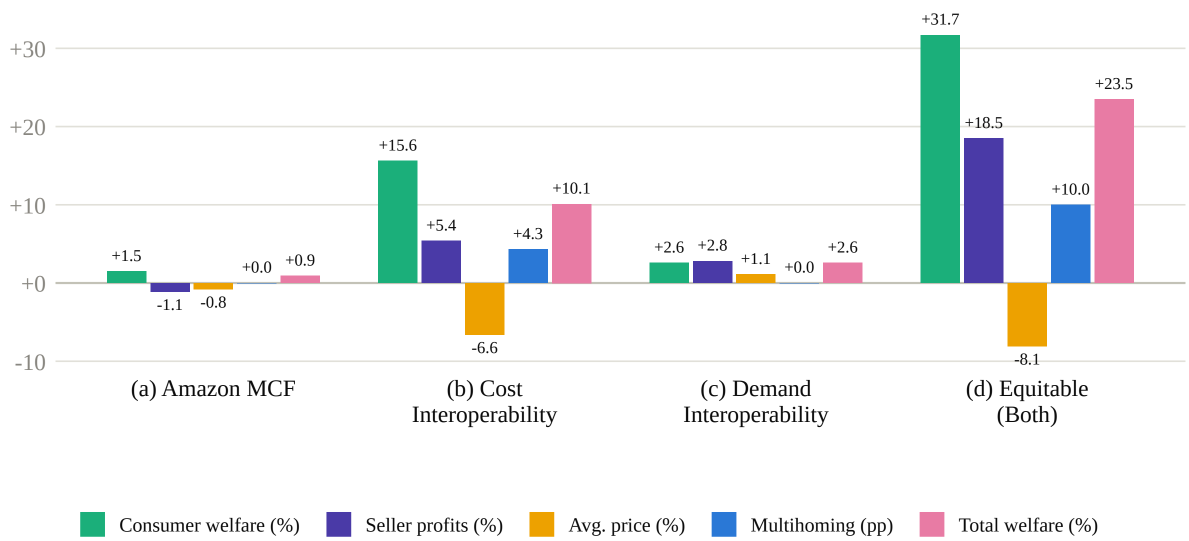
Notes. This figure shows kernel density estimates of organic search rank distributions by Amazon and Walmart. Sellers are divided into three categories: own-product retailer (i.e., 1P retailer), independent seller with integrated logistics, and independent seller with independent logistics.

Table A5: Fixed-Cost Estimates by Entry and Logistics Decision: Identified Sets

Decision $\mathbf{d}$		Fixed Cost $FC(\mathbf{d})$
Entry	Logistics	Identified Set ($1,000)
Amazon	Ind	[0.0, 0.0]
	FBA	[−17.5, 47.9]
Walmart	Ind	[−31.7, 0.0]
	WFS	[−31.7, 19.0]
Multihoming	Ind + Ind	[− 7.3, 56.0]
	FBA + Ind	[33.7, 76.8]
	Ind + WFS	[3.4, 35.1]
	FBA + WFS	[15.6, 47.6]

Notes. Exact values underlying Figure 9: identified sets of the nonparametric per-bundle fixed cost $FC(\mathbf{d})$, normalized relative to the Amazon-Ind bundle, $FC(d(1,0,0,0)) \equiv 0$, in $1,000 per product-month. See the notes to Figure 9 and Appendix Section G.1.1 for the estimation details.

Figure A13: Interoperable Logistics Counterfactuals



Notes. This figure shows the welfare and market outcomes of the interoperability analyses. Consumer welfare, seller profits, average prices, and total welfare are shown as% changes relative to the benchmark; the multihoming rate is shown as the%age-point change in the share of multihoming sellers. All platform logistics fees and commission rates are held at their observed levels in every panel. Panel (a) introduces Amazon's multi-channel fulfillment (MCF) service: multihoming sellers can fulfill Walmart orders through Amazon's logistics, pooling inventory, while paying the posted multi-channel fee; the service offers two-business-day shipping, similar to Walmart's logistics. Panel (b) removes the cost-side friction: the Walmart-side orders are charged the same fee that Amazon-side orders pay to Amazon logistics, instead of the higher multi-channel fee. Panel (c) removes the demand-side friction: Prime subscribers attain the same benefits from Amazon logistics on the Walmart side as on the Amazon side. Sellers who use Amazon logistics for Walmart orders pay the independent logistics fees. Panel (d) imposes equitable interoperability, combining the interventions of panels (b) and (c).