Algorithmic Ranking and Delivery Foreclosure in Retail Platforms: Evidence from Amazon and Mercado Libre

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Abstract

Retail platforms can tie search visibility to sellers' purchase of the platform's integrated warehousing and delivery services. Competition authorities are investigating this practice, but its welfare effects remain unquantified. Furthermore, when platforms compete for consumers, a rival can limit how much any one platform gains from favoring its own services, and a remedy imposed on one platform changes the incentives of the other. Using a panel of more than 415,000 search-result observations from Amazon and Mercado Libre, Mexico's two largest retail platforms, I estimate a structural model of platform competition in which consumers choose between platforms and search within them, sellers choose prices and delivery methods, and platforms set fees and ranking algorithms. Integrated delivery is higher quality than third-party alternatives but up to 96% more expensive, and both platforms rank it systematically higher. Separating Mercado Libre's delivery service from its platform lowers total surplus by 4.5% and consumer surplus on Amazon by 8.4%, because Amazon no longer faces a rival with a comparable integrated offering. Barring both platforms from favoring integrated delivery reduces the adoption of the integrated delivery by up to 9.1%, lowers prices by up to 8.0%, and raises total surplus by 3.7%, with consumer surplus raising 10.8% on Amazon and 7.2% on Mercado Libre.

Keywords: platform competition, algorithmic self-preferencing, vertical integration, tying, search frictions, e-commerce, antitrust

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1 Introduction

Retail platforms act as intermediaries between third-party sellers and consumers, mainly through ranking algorithms that decide which products appear, and in what order, when a consumer searches. Because platforms control this ranking channel, they can tie visibility to sellers' purchase of the platform's own complementary services, such as warehousing and delivery (e.g., Fulfilled by Amazon). The welfare effects of this practice are ambiguous. Platforms may use their rankings to favor sellers that adopt the tied service, hiding cheaper alternatives and raising the platform's pricing power over delivery, which increases sellers' costs and, in turn, consumer prices. Alternatively, the tied service may be genuinely better, which would justify both its prominence and its higher price. I show that which of these forces dominates depends largely on competition between platforms. Consumers choose where to search based on what they expect to find, so a platform whose rankings steer them toward more expensive products risks losing them to a rival. As a result, the effects of tying on one platform, and of any remedy imposed on it, depend on what the competing platform does.

I examine these forces empirically using collected data from the two largest retail platforms in Mexico and their delivery services: Amazon (FBA) and Mercado Libre (Full). I find evidence that products using the platforms' integrated delivery services are more expensive on average, yet they receive systematically better rankings in search results, moving up about 6 positions on Mercado Libre and 4 positions on Amazon relative to comparable products using third-party delivery, even after controlling for price, sales history, and reviews. I then develop a structural model that captures the strategic interactions between buyers, sellers, and platforms. The model enables me to estimate the unobserved quality and cost of integrated delivery as well as measure the effects of its tying to visibility on consumer and producer surplus. After estimating the model, I find that integrated delivery services are of higher quality than third-party alternatives and up to 84-95% more expensive for sellers.

This paper speaks directly to important ongoing antitrust enforcement: the U.S. Federal Trade Commission, the European Commission, and Mexico's COFECE have each investigated whether integrated-delivery ranking preferences constitute anticompetitive foreclosure.[1] Motivated by these interventions, I show that barring platforms from favoring their own delivery services in rankings raises total welfare, as sellers pull back from the more expensive integrated service and prices fall. The gains are highly asymmetric: because Mercado Libre's baseline algorithm favors integrated de-

[1] In September 2023, the FTC sued Amazon, alleging that tying Fulfillment by Amazon (FBA) to Prime eligibility constitutes an illegal monopolization scheme that raises costs for sellers and ultimately harms consumers through higher prices Federal Trade Commission (2023). The European Commission's 2019–2022 investigation into Amazon concluded that the platform's ranking algorithms systematically favored FBA products in the Buy Box, prompting binding commitments that Amazon treat all sellers equally regardless of fulfillment method (European Commission (2022)). In February 2024, Mexico's Federal Economic Competition Commission (COFECE) preliminary report found that Amazon and Mercado Libre, with about 85% of the market, favor sellers who use their fulfillment services (COFECE, 2024). Its September 2025 final resolution declared the platforms' Buy Box algorithms a barrier to competition but imposed no remedies (Comisión Federal de Competencia Económica, 2025).

livery more heavily than Amazon's, a common ranking rule requires a larger adjustment on Mercado Libre and shifts consumer market share toward Amazon. I then show that separating Mercado Libre's Full service from the platform, while leaving Amazon's ranking algorithm and FBA service unchanged, lowers total surplus and reduces consumer surplus on Amazon. These results show that platforms use their matching role to over-promote their own delivery services and extract rents from sellers, while competition from a rival platform limits a platform's ability to self-preference.

This paper makes three contributions. First, it studies a form of foreclosure that operates through tying rather than product-market substitution, a mechanism distinct from the *self-preferencing* of products studied in recent platform papers (Zhu and Liu, 2018, Dubé, 2022, Farronato et al., 2023). In my setting, foreclosure occurs in the delivery market as third-party logistics providers lose business when sellers switch to more expensive platform-integrated delivery to gain visibility. The welfare cost of this practice shows up as higher delivery fees passed through into consumer prices on top of potential biased matching. Second, I study how platform competition disciplines this practice. Almost all structural work on ranking bias studies Amazon alone; I observe two platforms that compete for the same consumers, which lets me ask how a common ranking rule affects platforms that start from different degrees of bias, and how much a rival platform's presence constrains self-preferencing. Third, I contribute new data: a panel of search results with more than 415,000 observations from 50 high-traffic keywords over 24 months. Because both platforms report monthly sales buckets, I estimate demand directly, without relying on the Pareto rank-to-sales mapping that similar papers assume when unit sales are unobserved (e.g. Chevalier and Goolsbee (2003), Zhu and Liu (2018), Yu (2024)).

Closest to my first contribution, Raval (2022) documents that in the US Amazon's ranking algorithm favors products fulfilled by Amazon even more strongly than products Amazon sells directly. My paper builds on this finding by developing an equilibrium model of platform ranking, seller delivery adoption, pricing, and consumer search, which lets me quantify how much of the resulting harm falls on sellers using third-party delivery versus consumers facing higher prices. Closest to my second contribution, Zhu and Liu (2018), Farronato et al. (2023), and more recent structural work (Lam, 2021, Hartzell and Haupt, 2024, Chen and Tsai, 2024), each study Amazon in isolation and show how ranking bias redistributes surplus between a platform and its own sellers, but not how it shapes competition between platforms. Because I observe Amazon and Mercado Libre in the same framework, I can show that the more-biased platform loses more market share once both are held to a common ranking standard, and that removing a rival's competing delivery service lets the platform behave more like an unconstrained incumbent. On the third contribution, I collect this data from Amazon and Mercado Libre search results using web scraping over the period from May 2023 to May 2025, recording product prices, monthly sales buckets, rankings, and delivery method for each observation. I supplement this with data on referral fees and the warehousing and delivery costs associated with FBA and Full, matched to the observed products, as well as aggregate data on platform market shares and market sizes from industry reports.

In Section 4, I develop a model where two competing platforms set commission fees and delivery fees for sellers, as well as subscription fees for buyers, and commit to a ranking algorithm, i.e. a mapping from observed and unobserved product characteristics to probabilities of each product being in a given rank, modeled as a rank-ordered logit. Sellers in the model choose prices for their products and decide whether to use the platform's first-party fulfillment services to maximize profits, anticipating how that choice affects their expected visibility and costs. Buyers then select which platform to join, search for a specific keyword, and purchase the product that maximizes their utility. Following recent papers (Lam, 2021, Yu, 2024) I model search in a reduced form by assuming that, exogenously, a product in the n-th rank position can only be examined by a fraction of the consumers in the market and that this fraction is decreasing in ranking. Consumers choose a platform based on their expected utility from purchasing a product after search and platform-specific affinity. The estimation results reveal substantial search frictions on both platforms: on Amazon, 62% of consumers consider only the first 20 products in search results, while on Mercado Libre, 22% of consumers stop searching within the first 20 products and the median search depth is around 50 products. Consumers are willing to pay about 25% extra for products using FBA or Full, but the ranking algorithms also favor higher-priced products over otherwise similar cheaper alternatives, so they reduce the visibility both of third-party delivery and of lower-priced products.

I then use the estimated model to conduct two sets of counterfactual exercises. The first asks what happens if both platforms are barred from favoring products that use their own integrated delivery service in rankings. I consider the adjustment under three progressively less restrictive equilibrium concepts. First, I hold seller prices and delivery choices fixed to isolate the direct matching effect of the ranking change. Consumer surplus increases slightly in the two platforms (2.53% on Mercado Libre and 4.53% on Amazon) as consumers face better choice sets. Second, I allow sellers to reoptimize prices and delivery choices. Since using integrated delivery does not lead to higher visibility in the counterfactual its use decreases by around 5% on both platforms and prices drop by 3.59% on Mercado Libre and 7.76% on Amazon. These first two equilibria assume that the platforms do not respond to the interventions so they can be read as benchmark cases to understand and measure the effect of each force in the model. However, platforms might respond to the new rankings by adjusting other parts of their business, which could dampen the intended effects of the policy.

In the third step I allow the platforms to adjust their commission rates under the new rankings. In this platform equilibrium, removing delivery-based ranking preferences increases total surplus by 3.71%. Integrated delivery adoption falls by 9.05% on Amazon and 5.30% on Mercado Libre as sellers lose the visibility incentive to use the more expensive integrated service. Prices fall by 7.99% on Amazon and 2.80% on Mercado Libre even when platforms increase their commission rate by 13.89% and 16.99% respectively, which raises sellers' costs. Consumer surplus rises on both platforms, it increases by 10.76% on Amazon and 7.20% on Mercado Libre. The effects on platform surplus are asymmetric. Amazon's consumer market share rises by 18.60%, while Mercado Libre's falls by 14.34%. Mercado Libre responds to the loss of delivery rents by raising its commission rate substantially, which offsets part of the consumer gain. Be-

cause Mercado Libre's baseline algorithm favors Full more aggressively than Amazon's favors FBA, a common regulatory standard requires a larger adjustment in Mercado Libre's rankings and shifts rents and consumers toward the less-biased platform. Thus, a formally neutral ranking rule has important distributional effects across competing platforms.

The second counterfactual asks how much platform competition itself disciplines self-preferencing. In this exercise, I separate Mercado Libre's Full service from the platform and assume that all sellers on Mercado Libre use third-party delivery services at the estimated costs and thus remove the ranking advantage from using Full, while leaving Amazon's ranking algorithm and FBA service unchanged. This exercise is not intended as a literal divestiture proposal. Instead, it approximates what happens to Amazon when the competitive constraint imposed by a rival delivery alternative is weakened. Mercado Libre's own consumers gain substantially from cheaper delivery, with consumer surplus raising 11.82%. Producers on Mercado Libre save on delivery so producer surplus on the platform goes up by 14.36% even as prices decrease by 11.71%. Mercado Libre wins market share but platform surplus goes down by 12.51%. Amazon loses 5.60% in market share but increases its surplus by 12.02% since they are collecting higher fees from prices that increase 7.40% compared to the baseline and sellers use FBA 21.68% more. Amazon consumer surplus falls by 8.40% due to the higher prices. Overall, total surplus falls by 4.47%. The comparison shows that the presence of a competing platform disciplines the exercise of market power even without direct regulation. The welfare value of this competitive constraint is therefore of a magnitude comparable to the direct welfare effect of regulating delivery-based ranking bias.

The counterfactuals distinguish two margins that are difficult to study in a single-platform setting. Direct ranking regulation limits the ability of vertically integrated platforms to charge sellers indirectly for visibility through costly fulfillment, while platform competition limits how aggressively a platform can exercise that market power in equilibrium. The results therefore suggest that competition authorities evaluating self-preferencing remedies should consider not only how a platform ranks products, but also how the conduct of competing platforms constrains those ranking incentives. It is worth noting that since the model assumes consumers and sellers single-home and holds the set of sellers and products on each platform fixed, it does not capture any offsetting effects from cross-platform search or from seller entry and exit so these counterfactual results are better read as an upper bound of the policy effects.

The rest of the paper is organized as follows. In Section 2, I describe how the platforms operate. Section 3 describes the data collection process and presents descriptive statistics and reduced-form results. In Section 4, I develop an equilibrium model that accounts for seller, buyer and platform's decisions. Section 5 presents the identification and estimation strategy. Section 6 presents the estimation results of the model presented in section 4 and Section 7 presents the counterfactual analysis. The paper concludes in Section 8.

1.1 Literature Review

This paper connects to five strands of literature. The first talks about the economics of platform design and platform competition. A foundational line of work examines how platform design choices, including ranking mechanisms, fee structures, and advertising, affect the welfare of consumers and sellers. Choi and Mela (2019) highlight the tension between advertising and transaction fee revenue streams, showing that product ranking and ad pricing mechanisms jointly influence user experience and platform profitability. Long et al. (2022) show that platforms can strategically use information obtained from ad auctions to refine organic rankings and set commission rates, driving competition among sellers. Most closely related to my empirical approach, Yu (2024) examines the welfare effects of sponsored product advertising on Amazon using a structural discrete choice model with search frictions, finding that eliminating sponsored ads could increase consumer surplus by 13% and seller profits by 14%, though these gains are sensitive to how platforms adjust their fee structures in response. My paper builds on this framework by incorporating platform ranking algorithms and seller delivery decisions into the structural model, as well as consumers choosing across platforms, allowing me to separately identify the role of algorithmic bias from genuine quality differences.

The second strand is the tying literature, which provides the theoretical foundation for the mechanism I study. Whinston (1990) shows that a firm can tie a complementary good to a market where it holds power, thereby foreclosing rivals in the tied good's market even absent any market power there, because tying reduces tied-good rivals' scale below the level needed to remain viable. Applied to platforms, the visibility a platform controls through ranking is the tying good, and integrated delivery is the tied good. A related theoretical literature models platforms directly as biased intermediaries: de Cornière and Taylor (2014) and de Cornière and Taylor (2019) show that an integrated intermediary has an incentive to bias its recommendations toward its own service even at the expense of match quality, and Hagiu and Jullien (2011) model why intermediaries divert search toward favored options in the first place. Cure et al. (2022), using web-scraped data from the search platform Kayak, document that affiliated online travel agencies receive more prominent placement than equally-priced rivals, a pattern similar to what I document for integrated delivery on Amazon and Mercado Libre, though in a different industry and without a structural model linking prominence to prices.

Closest to my setting, de Cornière et al. (2024) model the tying of an ancillary service, such as order fulfillment, to a platform's core intermediation function directly, showing that tying is profitable for the platform because it dampens sellers' bargaining power, even though it forces the ancillary service on sellers and consumers who may not value it highly. Iyengar et al. (2023) similarly model the introduction of a platform-owned fulfillment service and show its welfare effects are distributional, benefiting low-quality sellers and consumers while harming high-quality sellers, and that these effects are more pronounced when the platform itself owns the fulfillment arm rather than an independent logistics provider. Within this strand, Raval (2022) documents fulfillment bias in Amazon's ranking algorithm, and Li et al. (2025) is the closest theoretical paper, modeling rival platforms that differ in whether they offer an

integrated fulfillment service. My paper differs from this literature by structurally estimating the equilibrium link between ranking bias, delivery adoption, and prices, and by doing so for two platforms that actually compete with one another.

The third strand concerns vertical integration and self-preferencing of a platform's own competing products. The classical literature establishes that upstream firms can foreclose downstream rivals by raising their costs or restricting access to essential inputs (Ordover et al., 1990), and that vertical mergers can harm welfare even absent horizontal market power (Hart and Tirole, 1990). These insights were extended to incomplete-contract settings by Grossman and Hart (1986), who show that integration affects investment incentives by shifting residual control rights. In platform settings specifically, Lee (2013) shows that vertical integration and exclusive dealing can foreclose rivals and harm welfare even when the integrated product is of higher quality, since the platform can leverage its control over access to distort downstream competition; I build on his empirical strategy and allow consumers to choose which platform to join based on their expectations of the product choice set they will face on each. Empirically, Zhu and Liu (2018) examine Amazon's entry decisions into third-party product markets, finding that Amazon targets more successful products and that its entry discourages affected third-party sellers while reducing prices for consumers. Farronato et al. (2023) document that Amazon-branded products appear 30 to 60% higher in search results compared to third-party products with similar observable characteristics, providing reduced-form evidence of self-preferencing. Dubé (2022) offers a contrasting view, arguing that Amazon's private label strategy resembles standard supermarket private label practices rather than anticompetitive foreclosure. My paper studies a different mechanism than this literature: foreclosure through tying visibility to a complementary service, rather than through the platform's own entry into the product market.

The fourth strand tries to understand the effect of ranking algorithms on consumer choice, and increasingly uses structural methods to separate algorithmic bias from genuine quality differences. In a foundational paper, Ursu (2018) shows that ranking algorithms affect what consumers search but, conditional on search, do not affect purchases. Based on this evidence, the model in Section 4 assumes that, conditional on observing a product, its ranking does not enter the utility function. More recent papers use structural methods to understand optimal rankings from the platform or consumer welfare perspective (e.g. Compiani et al. (2024), Derakhshan et al. (2022)) and measure whether ranking algorithms are biased toward certain characteristics, e.g. delivery method, beyond what is optimal for matching (Reimers and Waldfogel, 2023). Closest to this strand, Musolff and Lee (2025), Hartzell and Haupt (2024), Lam (2021), and Chen and Tsai (2024) develop increasingly rich search-and-ranking models on Amazon to separate algorithmic bias from genuine quality differences. Because Amazon is the marketplace with the most accessible seller and ranking data, this literature is, by construction, about a single platform: it can speak to how ranking bias redistributes surplus between a platform and its own sellers, but not to how it shapes competition between platforms. A related limitation is that Amazon does not disclose unit sales in the US, so most of this literature either relies on prominence or click-through measures in place of sales (Farronato et al., 2023), or infers demand from Amazon's Best Seller Rank under an assumed Pareto relationship between rank and unit sales, an approach

dating back to Chevalier and Goolsbee (2003) and used throughout this structural work (Zhu and Liu, 2018, Musolff and Lee, 2025, Chen and Tsai, 2024, Lam, 2021). I instead observe monthly sales buckets directly reported in search results on both platforms, which lets me estimate demand without relying on a parametric mapping from ranks to sales. I follow some of these approaches to understand the platform's ranking decisions and to tease out the effect of the delivery method on rankings, conditional on other observable and unobservable product characteristics, but extend the setting to two competing platforms, which lets me separately identify the role of rankings from other sources of platform market power.

The fifth strand is the theoretical literature on competition between two-sided platforms, which motivates bringing two platforms into the same empirical framework rather than studying either in isolation. Armstrong (2006) and Rochet and Tirole (2003) show that platforms compete for users on one or both sides of the market and that the resulting market power depends on how easily users can multihome, and Armstrong and Wright (2007) formalize the "competitive bottleneck" case in which a platform retains market power over one side even under intense competition for the other. This literature predicts that a platform which distorts rankings more aggressively in favor of its own affiliated service should be relatively less attractive to the side bearing the cost of that distortion, and should therefore lose share to a less-distorting rival once regulation levels the playing field. To my knowledge this prediction has rarely been tested against data from platforms that compete directly for the same consumers and sellers.

2 Institutional Setting

Amazon and Mercado Libre are both large international retail platforms competing in the Mexican market. They have substantial presence for both consumers and sellers in Mexico. Together they have around 26% market share and close to 20 billion dollars of merchandise a year is sold through these platforms. In addition, according to the Mexican Competition authority COFECE (2024), 85% of Mexican online sellers use one or both platforms to sell their products. Similarly in the US, Amazon controls close to 40% of all online retail, so the insights from the Mexican market can also guide competition authorities in the US about how to better regulate the platform.

Table 1: Online Retail Market Shares of the Top Platforms in Mexico

Platform	**Market Share**	**GMV (2024)**	USA mkt. share
Mercado Libre	15.4%	∼$11 billion	–
Amazon	11.2%	∼$8 billion	37.6%
Walmart	<3%	–	6.4%

Source: Statista (2023, 2024)

Sellers of a large number of products, ranging from consumer electronics and clothes to furniture and groceries, list their products on the platforms. The platforms then collect fees for each product sold through their website and they also offer delivery services for sellers. They also offer a subscription service for consumers where, for a monthly

fee, consumers get free delivery of the products delivered by the platforms, as well as other perks such as streaming services.

Table 2: Summary of Fees and Subscription Prices of Amazon and Mercado Libre

	Amazon	**Mercado Libre**
Integrated Delivery Service:		
Program Name	Fulfilled By Amazon (FBA)	Full
Year Introduced	2015	2013
Seller Fees:		
Warehousing	\$0.35/mo. per cubic dm	\$0.011–\$0.50 per day
Shipping	\$50–\$65 + \$4/lb	\$131–\$3,146
Listing Fee	\$40 USD/month	None
Referral Fee	8–15% (min \$8)	8–16% (min \$25)
Consumer Subscriptions:		
Basic Tier	\$59	\$99
Medium Tier	\$129	\$149

Notes: Shipping fees information for Amazon obtained from `https://sell.amazon.com/pricing` and `https://www.mercadolibre.com.mx/ayuda/24253` for Mercado Libre. Subscription prices obtained from `https://www.amazon.com.mx/amazonprime` and `https://www.mercadolibre.com.mx/suscripciones/melimas`. Amazon referral fees range up to 45% for Amazon-branded devices. All prices in MXN unless otherwise noted.

On the seller side, both platforms charge commission fees and offer optional integrated delivery services, but differ in their entry requirements and operational structure (Table 2). Mercado Libre charges a category-specific commission fee per sale (8%-16%, minimum \$25 MXN) and offers optional advertisement packages (Classic or Premium), with free entry for sellers who opt out of advertising. The platform's Full service operates as follows: sellers send inventory to Mercado Libre warehouses and pay a daily storage fee ranging from \$0.011 to \$0.50 MXN depending on product dimensions; when orders arrive, the platform fulfills them and charges a delivery fee between \$131-\$3,146 MXN based on weight and dimensions, plus the standard sales commission. The sellers have an incentive to choose *Full* since the platform promises that it will lead to more visibility for the product and higher sales since consumers trust the delivery service. The platform also actively manages seller inventory decisions through its warehouse management system, alerting sellers when stock levels are low and could run out within days, or when inventory is excessive and could remain in storage beyond 8 weeks (`https://www.mercadolibre.com.mx/ayuda/40074`). This inventory optimization seems to work for sellers: in the data, the average Full product maintains approximately 30 units in stock while generating 242 monthly sales, implying sellers must replenish inventory roughly every 5 days to avoid running out of stock or unnecessary stocking expenses for excessive units.

Amazon's fulfillment structure imposes higher fixed costs. Sellers subscribe to a selling plan, paying either \$1 USD per item sold (individual plan) or \$40 USD monthly (professional plan), in addition to a category-specific commission (8%-15%, minimum \$8 MXN, with higher rates up to 45% for Amazon Device Accessories). Fulfilled by Ama-

zon (FBA) requires sellers to ship products in advance to Amazon warehouses, paying $0.35 MXN per cubic decimeter monthly for storage. Amazon then handles individual shipments to consumers, charging $50-$65 MXN base fee plus $4 MXN per pound for delivery. These operational differences, particularly Amazon's mandatory subscription fee and inventory management for each platform, create platform-specific entry barriers that discourage multihoming, as sellers must adapt inventory management, pricing strategies, and fulfillment logistics to each platform's distinct fee structure.

On the consumer side, both platforms offer subscription services that provide free delivery on orders fulfilled through their integrated services, creating indirect network effects that reinforce platform-specific seller strategies. The Amazon Prime subscription costs $129 MXN monthly (approximately $7.50 USD) and provides free one-day delivery on FBA orders, plus complementary video and audio streaming services and access to exclusive sales. Mercado Libre's Meli+ subscription costs $149 MXN per month, providing one-day free delivery and access to third-party streaming services, including Disney+. These platform-specific fulfillment ecosystems create strong incentives against seller multihoming. In the data, only 21% of products on Mercado Libre and 17% on Amazon appear on both platforms (see Section 3), and even when the same branded product appears on both, the sellers offering those products are different. The combination of platform-specific entry costs (subscription fees, listing optimization, inventory allocation), distinct fulfillment fee schedules, and different consumer subscription bases means that sellers effectively choose one primary platform and optimize their pricing and delivery decisions for that platform's specific environment. In the model presented in Section 4, I treat seller platform choice as given and focus on their within-platform strategy.

Both platforms employ ranking algorithms designed to present the most relevant products at the top of search results.[2] Though neither platform publicly discloses full algorithmic details, several factors are known to influence rankings across both platforms. First, product characteristics including pricing, product descriptions, delivery method, and search query relevance based on keywords. Second, user engagement metrics such as click-through rates and conversion rates, along with seller performance metrics including ratings, sales volume, and response rates. For sellers using the integrated delivery, the algorithms also incorporate inventory availability. Third, consumer-specific factors: purchase history affects personalized rankings, making each individual's search results somewhat unique. Finally, there is a random component in the ranking algorithm, so even if the same customer searches one keyword twice, they will get a slightly different ranking each time.

3 Data and Descriptive Results

I collect a panel of search results from Amazon and Mercado Libre in Mexico over 108 weeks, from May 2023 to May 2025 using web scraping. For each product in the search results, I observe its rank, title, description, price, delivery method, reported sales, cus-

[2]A product's ranking is its position in the search results. A lower ranking indicates the product appears higher on the page and therefore has greater visibility.

tomer reviews, and the seller offering it, including the seller's name, reputation score, and total sales. I supplement these data with the commission rates and fulfillment fees each platform charges, matched to the observed products, and with aggregate market shares and market sizes from industry reports. This section describes how the search results were collected (Section 3.1), how keywords and markets are defined (Section 3.2), how the main variables are constructed (Section 3.3), and the resulting sample (Sections 3.4–3.5).

3.1 Data Collection

I collect the data by web scraping the desktop version of each platform's search results. Every week, for every keyword in the sample, I run one search from each of Mexico's three largest metropolitan areas: Mexico City, Monterrey, and Guadalajara. I set the location through the proxy used for each search, so the results, the delivery promises, and the availability of each product correspond to a buyer in that city. I average a product's rank across the three searches and treat the product as using integrated delivery if it does so in any of them.

Each search records up to seven pages of results. The desktop interface shows approximately 50 products per page, and I number ranks continuously across pages, so the first product on the second page has rank 51. Because the structural analysis uses only the top 50 products in each search (Section 3.5), these products almost always appear on the first page, and the page break plays essentially no role in the estimation. Sponsored listings are part of the ranking. Both platforms insert advertised products into the organic results. These products are placed by an ad auction and not by the organic recommendation algorithm of each platform, however, consumers still browse to them in the order the platform presents them.

Three features of the collection matter for interpreting the rankings. First, each search uses a new proxy with no cookies, account, or browsing history, so the observed ordering is the platform's default algorithm for a buyer with no history and no subscription. Using a new proxy each time allows me to estimate how the algorithm weights product characteristics since the data does not capture any personalization effect. Furthermore, I cannot observe how rankings differ for Prime or Meli+ subscribers. Because these subscribers receive free and faster delivery only on integrated-delivery items, any personalization toward their past purchases is likely to favor integrated delivery further, so the bias I estimate is plausibly a lower bound for subscribers.

Second, all searches run on weekdays, but the time of day is not fixed across weeks. Within-day timing adds noise to the observed rankings. I have no reason to expect this noise to be correlated with a product's delivery method, and the monthly aggregation described in Section 3.3 averages much of it out. The remaining stochastic component, evidenced by ranking volatility even for products with stable characteristics (I later show that products change ranks an average of 12-18 times over the sample period) provides identifying variation for separating the causal effect of ranking position on sales from reverse causality, as detailed in the identification strategy in Section 5.1.2.

Third, I observe desktop rankings, while most online shopping traffic in Mexico comes from mobile devices: about 74% of traffic during the 2025 Hot Sale campaign was mobile (Asociación Mexicana de Venta Online, 2025). The mobile apps display results as a continuous scroll rather than in pages so my estimates of the ranking algorithm might not reflect the positions for mobile apps. There is evidence that suggests that rankings matter more on mobile than on desktop: Ghose et al. (2013) find that search costs are higher and ranking effects stronger on mobile devices, consistent with a phone screen showing only a few products at a time. Since I observe aggregate sales data coming from both desktop and mobile, the estimates of search frictions and utility parameters are representative of both consumer types.

3.2 Keywords and Market Definition

The search keywords come from Mercado Libre's weekly lists of its 20 most popular and 20 fastest-growing searches (`https://tendencias.mercadolibre.com.mx/`). The most-popular list is stable over the sample period: I observe 35 distinct keywords on it over two years. I complement these with 15 of the fastest-growing keywords, so the sample includes both products with consistently high sales and products that become popular for a limited period, such as a newly released phone. Amazon Mexico publishes best-seller lists but not its most frequent searches, so Mercado Libre's lists are the only available source of search terms. I use the same keywords on both platforms. In total I observe 97 keywords; the 50 in the main sample are those that appear consistently enough to form a balanced panel, and the remaining keywords enter and exit the trends lists.

Table 9 in the Appendix lists the 50 keywords with their categories and market sizes. They span electronics, home goods and appliances, apparel, footwear, and sporting goods, but sales are concentrated in a few categories and keywords. Electronics keywords account for about 64% of total market size. The top 15 largest keywords account for about 81%, and the top 25 for about 94%. Because welfare results are aggregated using market sizes, these keywords carry most of the weight in the counterfactuals.

Selecting high-traffic keywords is deliberate. These are the markets where ranking position is most valuable and where steering toward integrated delivery has the largest consequences. It also means the estimates should be read as describing high-volume searches rather than long-tail ones. In my sample, products on Mercado Libre have higher average sales than those on Amazon, consistent with Mercado Libre being the larger platform in Mexico. I define a market as a keyword–month on each platform. The raw data are weekly, and I aggregate them to the monthly level for estimation (Section 3.3).

3.3 Variable Construction

Sales. Neither platform reports exact unit sales. Instead, each listing displays a threshold on last month's sales, such as '+25 sold last month.' The thresholds are not evenly spaced, but they come from a fixed set of values (10, 25, 50, 100, 250, 500, 1,000) so each displayed threshold maps to an interval running up to the next threshold. For example, '+25' means between 25 and 50 units. I use the midpoint of each interval as the sales measure. For the highest threshold, which has no upper bound, I assign the threshold times 1.5. Listings that display no sales threshold are assigned the midpoint of zero and the lowest threshold. For Amazon, I validate this measure against Keepa.com, which tracks sales and prices independently. Because sales are reported as monthly ranges and these ranges change only every few weeks, I aggregate all variables to the monthly level, which matches the reporting period of the sales data and reduces noise from week-to-week fluctuations and from the timing of each search. Observing sales directly, even in ranges, is an important difference from most work on Amazon rankings, which infers unit sales from Best Seller Ranks using an assumed Pareto relationship (Chevalier and Goolsbee, 2003).

Delivery method. I classify a product as using integrated delivery from the delivery information on its listing. On Amazon, a product uses integrated delivery (FBA) if the listing states that it is 'Enviado por Amazon' (*shipped by Amazon*). On Mercado Libre, a product uses integrated delivery if it carries the *Full* badge, meaning it ships from Mercado Libre's own warehouses. Every other product is classified as third-party delivery. The comparison throughout the paper is therefore between fulfillment from the platform's own warehouses and every other delivery arrangement.

Prices and shipping. The price I record is the price a buyer faces at the time of the search, including promotional discounts and any shipping fee charged to the buyer. In practice, buyers in my sample rarely pay shipping directly. On Mercado Libre, free shipping is mandatory for new items priced above $299 MXN, and the seller pays for it. On Amazon, Prime members receive free shipping on eligible items, and non-members receive it above a minimum order value. Only 15.49% of observations on Amazon and 20.57% of observations on Mercado Libre in my sample are priced below $299 MXN. Delivery costs are therefore mostly borne by sellers and passed through to buyers in the product price rather than charged separately, which is how the model in Section 4 treats them.

Sellers, Buy Box, and product identifiers. On both platforms, several sellers can offer the same product, and the search result shows the seller that holds the Buy Box. I assume buyers purchase from the Buy Box seller. The same product can appear at different positions in a search with a different Buy Box seller at each position, so I treat each product-seller combination as a separate listing. I identify products by their platform identifiers (Amazon's ASIN and Mercado Libre's item ID) and sellers by the name of the Buy Box seller, so a listing is a product-seller pair. The sample contains 12,950 such pairs.

Fees. Both platforms charge commissions that vary by product category and fulfillment fees that vary with item size and weight. Each listing has a category tree, chosen by the seller when posting it, that runs from a root category (e.g., electronics) through subcategories (e.g., speakers) to the finest category (e.g., portable Bluetooth speakers). I collect each platform's commission rate by subcategory and assign it to the corresponding products.[3] For fulfillment fees, I match each product to the warehousing and delivery fees in the platform's published schedules, using the item description and the available package size information. Because sellers keep a low ratio of stock to sales, I include warehousing costs in the per-unit delivery cost.

3.4 Descriptive Statistics

Table 3 presents descriptive statistics for the primary sample. The data covers 186,240 product-week observations for Mercado Libre and 228,910 for Amazon. On average, I observe 351 products sold by 77 different sellers per keyword search on Amazon. On Mercado Libre, the average search returns 250 products with approximately 120 distinct sellers.

Table 3: Descriptive Statistics

	Mercado Libre		**Amazon**	
Variable	Mean	(Std. Dev.)	Mean	(Std. Dev.)
Market Structure:				
Products per Keyword	250.32	(143.96)	351.23	(154.80)
Sellers per Keyword	119.86	(92.75)	77.74	(177.45)
Multihoming products (%)	21.01	(10.16)	17.13	(13.89)
Multihoming sales (%)	9.18	(1.70)	16.78	(1.02)
Product Characteristics:				
Price (MXN)	4,207.97	(3,924.90)	2,564.27	(3,437.87)
Monthly Sales (units)	242.47	(371.91)	106.33	(275.99)
Number of Reviews	330.48	(1,991.29)	223.37	(1,694.97)
Rating (1-5 stars)	4.61	(0.36)	4.31	(0.32)
Commission Rate	15.03%	(4.90)	13.07%	(2.77)
First-Party Delivery (%)	50.66	(49.87)	66.35	(38.31)
FBA/Full Delivery Cost	127.35	(143.21)	160.4	(143.56)
Full Product Stock	30.60	(20.81)	-	-
Observations	186,240		228,910	

Notes: Sample covers 415,150 observations from 12,950 unique seller-product pairs across 50 search keywords tracked over 24 months (May 2023-May 2025). Standard deviations in parentheses. Products denotes unique product listings per keyword-week. Sellers counts distinct seller identities offering products within each keyword. Monthly Sales represents average monthly unit sales as reported by platforms. First-Party Delivery refers to Full (Mercado Libre) and FBA (Amazon). All statistics computed at the product-month level.

[3]Commission rate data are available at `https://vender.amazon.com.mx/precios` for Amazon and `https://vendedores.mercadolibre.com.mx/` for Mercado Libre.

The platforms show differences in pricing and sales patterns. The average item price for products sold on Amazon is $2,564 (MXN) compared to Mercado Libre's $4,208. Average monthly sales on Mercado Libre are 242 units compared to Amazon's 106 units. Sales dispersion is higher on Mercado Libre (std. dev. 371.91) relative to Amazon (275.99). Importantly, 66% of products on Amazon use Fulfillment By *Amazon* and 51% of products on Mercado Libre use *Full*. Other papers (e.g. Dubé (2022), Farronato et al. (2023)) have looked at Amazon acting as a seller and how it affects product market competition. In Mexico, Mercado Libre never acts as a seller, and in my data, less than 1% of all sales come from products sold directly by Amazon so I abstract from that part of their business and treat products sold by Amazon as if sold by an independent seller in my main results. Sales are concentrated among a small number of sellers. Although the average keyword has about 120 sellers on Mercado Libre and 78 on Amazon, the top 10 sellers in each keyword account for 84.9% of sales on Mercado Libre and 80.3% on Amazon.[4]

Figure 7 in the Appendix presents prices, sales and use of first-party delivery across top 25 keyword searches by sales. The use of FBA and Full varies across markets, this variation will be useful when determining the effect of the use of these delivery options on market outcomes. Higher prices in Mercado Libre are correlated with higher prices on Amazon, while sales are slightly negatively correlated. This is evidence that the search results of the two platforms display products that are substitutes.

To assess the extent of seller and product multihoming across platforms, I implement a two-stage matching procedure. First, I match products across Amazon and Mercado Libre by comparing product titles using fuzzy string matching (Levenshtein distance) with a threshold of 85% similarity, supplemented by exact matches on brand names and product descriptions when available. This conservative approach yields an overall match rate of 21.0% for Mercado Libre products and 17.13% for Amazon products (Table 3), indicating limited product-level multihoming. Second, I attempt to match sellers across platforms by comparing seller usernames and store names that sell similar products. However, sellers on both platforms choose their own store identifiers (which can be arbitrary usernames, business names, or individual names) making systematic seller matching infeasible without additional external data sources. I observe no reliable seller matches across platforms in the sample. When the same branded product does appear on both platforms (the 21% overlap), it is typically offered by different sellers or by the same manufacturer using different fulfillment strategies tailored to each platform's fee structure. This limited multihoming at both the product and seller levels supports the modeling assumption in Section 4 that sellers select a primary platform and optimize their pricing and delivery decisions for that platform's specific environment, rather than maintaining active presence and coordinating strategies across both marketplaces.

[4]In Section 7, in the counterfactuals, I allow only the largest sellers in each market to re-optimize to lower the computational burden, because of the high concentration of these sellers their response captures most of the market's response.

3.5 Estimation Sample

For the main estimation results of the model presented in the following section, I keep the top 50 products by sales of each keyword-week pair as a way of keeping the model computationally tractable. I justify this exclusion criterion with Figure 6, in the Appendix, where we observe that the top 50 products account for 85% of the market share in Mercado Libre and 93% in Amazon on average across all keywords. I then define the remaining products as the outside option in the model. I aggregate the data at the monthly level for estimation. I also drop products that appear in fewer than three consecutive weeks of search results. Table 10 in the Appendix presents descriptive statistics for this restricted sample. Most statistics are similar to the full sample, though sales and reviews are naturally higher, since the restriction selects the best-performing products. Importantly, FBA adoption among Amazon's top 50 products is lower than in the full sample, while Full adoption on Mercado Libre is higher in the restricted sample.

3.6 Product Time Variation

Table 4 documents the frequency of changes in key product characteristics during the observation period. Changes are measured as transitions where a variable's value at a given month differs from its value in the previous month within each product's time series. I document the distribution of these transitions across the platforms in Figure 8 in the Appendix. The statistics reveal substantial variation in product characteristics over time, indicating that sellers actively adjust prices, fulfillment options, and other strategic variables in response to competitive pressures or platform changes in pricing.

Table 4: Change in Product Characteristics Over Time

	Mercado Libre			**Amazon**		
Variable	Min	Mean	Max	Min	Mean	Max
Price Changes	1	4.29	24	3	13.91	24
Delivery Changes	1	2.16	13	1	2.99	20
Sales Changes	1	1.98	24	2	5.55	24
Share Changes	2	5.66	23	5	10.68	24
Rank Changes	4	12.20	24	5	18.52	24

Notes: Table reports the minimum, mean, and maximum number of transitions in product characteristics during the 24 month observation period. A change is defined as a transition where the variable value at month t differs from its value at month $t-1$ for each product. Price Changes counts transitions in listed prices. Full/FBA Changes counts switches between first-party fulfillment (Full on Mercado Libre, FBA on Amazon) and seller fulfillment. Sales Level Changes counts transitions between sales buckets. Market Share Changes counts transitions in within-keyword market share. Search Rank Changes counts movements in search result position. Statistics computed at the product level.

Price adjustments occur frequently on both platforms, though considerably more frequently on Amazon. Products on Mercado Libre change prices an average of 4.29 times during the sample period, with some products changing prices as many as 24 times (every month). Amazon products average 13.91 price changes and a maximum of 24 changes. Changes in the fulfillment method are less frequent than price adjustments, but still occur for all products. On Mercado Libre, products switch between Full and

non-Full delivery an average of 2.16 times, with a maximum of 13 switches. Amazon products exhibit slightly more changes in fulfillment, averaging around 3 changes between FBA and non-FBA, with a maximum of 20 changes. The variation in price and delivery methods across time but within products helps to identify the consumer's price sensitivity and the perceived quality of the integrated delivery method for each platform.

Sales and market share exhibit moderate variation over time. Products experience an average of 1.98 sales level changes on Mercado Libre and 5.55 on Amazon, measured as transitions between sales buckets. Market share changes occur more frequently, averaging 5.66 transitions per product on Mercado Libre and 10.68 on Amazon, with maximum values reaching 24 changes on both platforms. The higher frequency of market share changes relative to sales changes reflects both sales changes and compositional changes in the set of competing products within each keyword search.

Search ranking displays the highest volatility among all observed variables. Products on both platforms move across different rank positions an average of 12-18 times, with some products changing ranks as many as 24 times during the observation period. This substantial ranking variation provides the key source of identifying variation for estimating the determinants of search rank and their effects, as it reflects both algorithm reordering in response to product characteristic changes and exogenous shocks within keyword markets.

3.7 Product Characteristics by Delivery Method and Algorithmic Bias

Table 5: Balance of Product Characteristics: Integrated vs. Third-Party Delivery

	Mercado Libre			Amazon		
Variable	Full	Third-Party	Difference	FBA	Third-Party	Difference
Price (MXN)	4,841.52	3,015.72	1,825.80*** (72.35)	3,059.89	2,702.10	357.80*** (99.96)
Monthly Sales (units)	696.13	253.93	442.20*** (12.89)	111.51	108.41	3.11 (6.95)
Number of Reviews	217.09	193.31	23.78 (53.32)	337.85	224.30	113.55*** (33.28)
Rating (1-5 stars)	4.63	4.66	-0.04*** (0.01)	4.28	4.34	-0.06*** (0.02)
Search Rank	61.30	69.19	-7.88*** (0.67)	59.96	68.85	-8.88*** (0.89)
Observations	94,349	91,891	186,240	151,882	77,028	228,910

Notes: Sample means for products using integrated delivery (Full on Mercado Libre, FBA on Amazon) versus third-party delivery. Difference is Integrated − Third-Party, with the standard error of a Welch two-sample t-test in parentheses below. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In this subsection, I document that products using Full and FBA are statistically different from products using third-party delivery, and that they are also treated differently in the platforms' rankings. However, measuring ranking bias is an endogeneity

problem: platforms may rank products with higher unobserved quality more favorably, so a product's use of integrated delivery could be correlated with unobserved characteristics that independently affect its ranking. The regression presented below is therefore only a first approximation to the extent of bias, since it does not fully address this concern; the structural model developed in Section 4 explicitly tackles this endogeneity using the identification strategy described in Section 5.1.2.

Table 5 compares product characteristics across delivery methods on each platform. On both platforms, products using integrated delivery are shown in statistically significant better search positions: FBA products rank roughly 9 positions higher than third-party alternatives on Amazon, and Full products rank almost 8 positions higher on Mercado Libre, a first indication of the ranking advantage documented more formally below. Products using Full and FBA also differ from those using third-party delivery on other dimensions: they are priced higher on both platforms, and on Mercado Libre they generate substantially higher monthly sales. These differences imply that simply comparing rankings across delivery methods to measure algorithmic bias would ignore the effect of prices, sales and reviews on the rankings. On Mercado Libre, for example, the advantage of Full in ranking could come from higher sales. Based on Reimers and Waldfogel (2023), I regress the search rank on delivery status, controlling for product characteristics such as past sales and prices, to have an initial measure of algorithmic bias towards Full and FBA in the platforms' search rankings.

Table 6: Reimers-Waldfogel Measures of Search Bias

	Dependent Variable: Search Rank	
	Amazon	**Mercado Libre**
Log Price	7.075***	7.679***
	(0.193)	(0.138)
Market Share	-81.672***	-153.289***
	(13.519)	(23.810)
FBA/Full Delivery	-15.037***	-24.867***
	(2.562)	(2.120)
Keyword FE	YES	YES
Time FE	YES	YES
Observations	228,910	186,240
R-squared	0.513	0.524
Adjusted R-squared	0.513	0.524

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The dependent variable is product rank within search results. Log Price is the natural logarithm of product price. Market Share is the product's share of total keyword sales. FBA/Full Delivery indicates whether the product is delivered by the platform's integrated delivery services. All regressions include search keyword and time fixed effects. Standard errors are clustered at the keyword level.

Table 6 presents the results. In the absence of bias, optimal search result rankings should maximize a weighted sum of consumer and seller welfare. Deviations from this welfare-maximizing frontier occur when rankings exhibit bias toward specific product characteristics, such as *FBA* or *Full* delivery services. To test for the presence of such bias, Reimers and Waldfogel (2023) propose regressing product rankings on log prices, market shares, and the suspected bias source; in our case, *Full* or *FBA* delivery status. A coefficient statistically different from zero on the first-party delivery variable constitutes evidence of ranking bias since it implies that similar products are treated differently when using integrated delivery. The regression results reveal that both *FBA* and *Full* delivery coefficients are negative and statistically significant, indicating that utilization of these services effectively improves product rankings. Specifically, products fulfilled by the platform are systematically positioned in more favorable search positions, suggesting preferential treatment in the ranking algorithm.

4 Structural Model

In this section, I develop a structural model that captures the strategic interactions among buyers, sellers, and platforms. In the model, two competing platforms set commission fees and delivery fees for sellers, as well as subscription fees for buyers. Sellers choose prices for their products and decide whether to use the platform's first-party fulfillment services to maximize profits. Buyers then select which platform to join, search for a specific keyword, and purchase the product that maximizes their utility. This framework allows me to analyze how vertical integration between platforms and fulfillment services affects market outcomes and welfare.

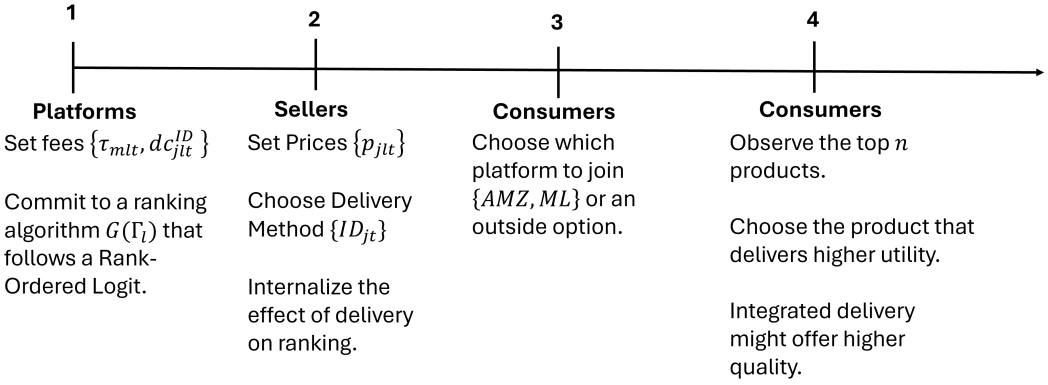


Figure 1: Model Timeline.

Formally, there are $t = 1, ..., T$ time periods and M markets (keywords) per period. In each period, two platforms $l \in \{AMZ, ML\}$ host sets of sellers $s \in S_{lt}$ who offer differentiated products. In each period there is a continuum of consumers indexed by $i \in I$.

Each time period, the agents play a 4-stage game represented in Figure 1. In stage 1, platforms commit to a ranking algorithm G that maps product characteristics to a distribution of ranks, then set market-specific commission fees τ_{mlt} and delivery fees

dc_{jlt}^{ID} for sellers using their integrated delivery services and a subscription fee b_{lt} for buyers. In stage 2, sellers optimally set prices and choose delivery methods given the platforms' fees and ranking algorithm. In stage 3, consumers decide whether to join a platform to search for products or select an outside option. In stage 4, consumers who joined a platform search for a keyword and select the product that maximizes their utility from their choice set.

In the remainder of this section, I describe each stage of the game in reverse order, beginning with stage 4 and proceeding backward to stage 1.

4.1 Buyer Side

4.1.1 Stage 4

Let J_{mlt} denote the set of horizontally differentiated products available on platform l in market m at time t. I index products by j, with $j = 0$ representing an outside good. In stage 4, consumers who join a platform search for a keyword and select the product that maximizes their utility from their choice set. I assume that the platform's ranking algorithm affects consumer choice through search frictions.

Following Yu (2024), I incorporate these frictions in a reduced-form way by assuming that, exogenously, a product in the $n-$th position can only be examined by a fraction of the consumers in the market and that this fraction is decreasing in ranking. Formally, let Γ_{mlt} denote the product ranking on platform l, which displays the J_{mlt} products in sequential order. For any position $n \in \{1, 2, ..., J_{mlt}\}$, define $J_n(\Gamma_{mlt})$ as the consideration set containing all products ranked from position 1 through position n on platform l. Let λ_{nml} represent the fraction of buyers who examine at least the first n products, where the sequence $\lambda_{1ml} \geq \lambda_{2ml} \geq ... \geq \lambda_{nml} > \lambda_{N+1ml} = 0$ reflects diminishing visibility as consumers progress down the search results. Consequently, the difference $(\lambda_{nml} - \lambda_{n+1ml})$ quantifies the proportion of consumers who examine exactly n products and make their purchase decision based solely on that consideration set. The first few products in search results receive significantly more visibility, creating a substantial advantage for higher-ranked items.

For the main results, I follow Yu (2024) and parameterize the fraction of consumers who examine at least the first n products using an exponential decay function $\lambda_{nml} = 1/\exp(\beta_{ml}(n-1))$ for $n \leq N$ and $\lambda_{nml} = 0$ for $n \geq N+1$. When $\beta_{ml} = 0$, there are no search frictions on platform l and a product's rank does not affect its sales. A larger β_{ml} implies that, for a given market, a greater share of consumers examine only top-ranked products. In the online Appendix I, I relax this assumption and allow λ_{nml} to be non-parametrically identified. Since the estimates are robust to this relaxation, I retain the parametric specification in the main body of the paper.

The indirect utility of consumer i from purchasing product j in market m on plat-

form l is specified as:

$$u_{ijmlt} = \underbrace{\alpha_{ml} p_{jlt} + \gamma_{ml} ID_{jlt} + \psi_j + \psi_t + \xi_{jlt}}_{\delta_{jlt}} + \epsilon_{ijt} \tag{1}$$

where p_{jlt} represents the price of product j at time t on platform l, and α_{ml} captures the price sensitivity of consumers in market m on platform l. ID_{jlt} is an indicator variable equal to 1 if product j uses the platform's first-party fulfillment service at time t, and γ_{ml} captures the platform-specific utility benefit consumers derive from products fulfilled by the platform (e.g., better customer service). ψ_j is a product fixed effect, and ψ_t represents time fixed effects. ξ_{jlt} captures unobserved product quality, and ϵ_{ijt} is an idiosyncratic preference shock assumed to follow a Type I extreme value distribution.

The assumption that consumers cannot multi-home, that is, they must choose a single platform for their search, reflects that consumers typically concentrate their search activities on a single platform. The mean utility component δ_{jlt} is platform-specific, so the same product may deliver different utility levels depending on which platform it is purchased from due to platform-specific prices, sellers' fulfillment choices, and consumer heterogeneity.

Let $\mathbf{p}_{mlt}, \mathbf{ID}_{mlt}$ denote the vectors of prices and delivery choices on market m, platform l at time t. The market share of product j can be expressed as:

$$s_{jlt}(\mathbf{p}_{mlt}, \mathbf{ID}_{mlt}, \Gamma_{mlt}) = \sum_{n=1}^{J_{mlt}} 1(j \in J_n(\Gamma_{mlt}))(\lambda_{nml} - \lambda_{n+1ml}) \frac{\exp(\delta_{jlt})}{1 + \sum_{j' \in J_n(\Gamma_{mlt})} \exp(\delta_{j'lt})} \tag{2}$$

This equation has an intuitive interpretation: for each consideration set J_n that includes product j, we calculate the probability that a consumer who examines exactly n products chooses product j, weighted by the proportion of such consumers $(\lambda_{nml} - \lambda_{mn+1l})$. The indicator function $1(j \in J_n(\Gamma_{mlt}))$ ensures that product j is only considered if it appears in the top n positions. The conditional choice probability follows the standard multinomial logit form, where consumers choose the product with the highest utility among those they have examined.

4.1.2 Stage 3

I follow Lee (2013) and assume that the expected utility for consumer i who selects platform l to shop in market m at time t is given by the platform's mean utility δ_l plus the expected utility from purchasing their preferred product on that platform:

$$u_{imlt} = \delta_l - b_{lt} + E[\max_j \{\delta_{jlt} + \epsilon_{ijt}\} | l] + \epsilon_{ilt}$$

where $\{\epsilon_{ijt}, \epsilon_{ilt}\}$ are independent Type I extreme value idiosyncratic preference shocks for platforms and products. I normalize the utility of the outside option to $u_{i0t} = \epsilon_{i0t}$.

At this stage, the expected maximum utility averages over consumers' consideration sets, idiosyncratic preference shocks, and the distribution of rankings:

$$\mathbb{E}\left[\max_{j}\{\delta_{jlt}+\epsilon_{ijt}\} \mid l\right] = \int \sum_{n=1}^{J_{mlt}} (\lambda_{nml}-\lambda_{n+1,ml}) \log\left[1+\sum_{j\in J_n(\Gamma_{mlt})}\exp(\delta_{jlt})\right] dG(\Gamma_{mlt})+\gamma_{\mathrm{E}}. \tag{3}$$

Here, $\gamma_{\mathrm{E}} \approx 0.57721$ is the Euler–Mascheroni constant, resulting from integrating over the extreme-value shocks. The maximum is taken over the consumer's realized consideration set, including the outside good, whose deterministic utility is normalized to zero. Consumers join the platform that delivers the highest expected utility or choose the outside option.

4.2 Seller Side

4.2.1 Stage 2

In stage 2, each seller $s \in S_{lt}$ on platform l offers a set of products J_{st} at time t, sets prices p_{jlt} for each product, and decides whether to utilize the platform's first-party fulfillment services. Let $ID_{jlt} = 1$ if product j is fulfilled by the platform's integrated delivery service and $ID_{jlt} = 0$ otherwise.

I assume that sellers do not know the exact ranking their products will receive in period t but know the platform's ranking algorithm. Specifically, let $G : P \times ID \times X \to \Delta(\Gamma)$ denote a ranking function that maps product prices, delivery methods, and other observable characteristics to a distribution over positions in the search results. The sellers know G but do not know their exact position in the rankings since G is a stochastic function. Sellers then form an expectation of the market share of product j given the ranking algorithm as follows:

$$s^{e}_{jlt}(\mathbf{p}_{mlt}, \mathbf{ID}_{mlt}) = \int s_{jlt}(\mathbf{p}_{mlt}, \mathbf{ID}_{mlt}, \Gamma_l) dG(\Gamma_{mlt}) \tag{4}$$

The expected profit function for seller s on platform l is then specified as:

$$\pi_{sl} = \sum_{t}\sum_{j\in J_{st}} \left[(1-\tau_{mlt})p_{jlt} - mc_{jt} - dc^{ID}_{jlt} ID_{jlt} - dc^{tp}_{jt}(1-ID_{jlt})\right] q_{jmlt}(\mathbf{p}_{mlt}, \mathbf{ID}_{mlt}) - FC_s$$

where mc_{jt} denotes the marginal production cost of the product j at time t, dc^{ID}_{jlt} is the per-unit cost of delivery charged by the platform when using the integrated service, dc^{tp}_{jt} represents the per-unit cost when using third-party delivery services. I define a seller's total expected sales as $q_{jmlt}(\mathbf{p}_{mlt}, \mathbf{ID}_{mlt}) \equiv M_{mt} s^{e}_{jlt}(\mathbf{p}_{mlt}, \mathbf{ID}_{mlt}) s_{mlt}$ with M_{mt} the size of the market m at time t and s_{mlt} the market share of the corresponding platform, and FC_s represents the fixed costs incurred by the seller s.

The supply-side model captures the key trade-off sellers face: first-party fulfillment may entail higher costs but could lead to preferential ranking by the platform, which in turn increases their expected sales q_{jmlt}.

4.3 Platforms

4.3.1 Stage 1

As is standard in the literature (e.g., Gutierrez (2021); Castillo (2025); Yu (2024)), I assume that the platform sets commission rates τ_{mlt} and delivery prices dc^{ID}_{jlt} to maximize a combination of short-term revenues, consumer surplus, and seller profits.

$$\max_{\tau_{mlt}, dc^{ID}_{jlt}, G(\Gamma_{mlt})} \quad \sum_j (\tau_{mlt} p_{jlt} + dc^{ID}_{jlt} ID_{jlt}) q_{jmlt}(\mathbf{p}_{mlt}, \mathbf{ID}_{mlt}) + \mu^C_{ml} CS(\tau, dc^{ID}) + \mu^P_{ml} PS(\tau, dc^{ID}) \tag{5}$$

where $\mu^C_{ml}, \mu^P_{ml} \geq 0$ represent the weights that the platform assigns to consumer and seller surplus on each market, respectively.

4.3.2 Ranking Algorithm

The platform also commits to a ranking algorithm $G : P \times ID \times X \to \Delta(\Gamma)$ which denotes the ranking function that maps product prices, delivery methods, and other observable characteristics to a distribution over positions in the search results. While the platform could in principle choose from a vast space of ranking algorithms, I impose structure by assuming products are ranked according to a Rank-Ordered Logit (ROL) model (Beggs et al. (1981)).[5] This specification is flexible yet tractable, allowing the ranking to depend on multiple product characteristics.

In this model, the platform assigns a value or index to each product that is a linear function of its characteristics $(p_{jlt}, ID_{jlt}, X_{jlt})$ plus a Type I extreme value unobserved shock:

$$value_{jmlt}(p_{jlt}, ID_{jlt}, X_{jmlt}) = \underbrace{\beta_p p_{jlt} + \beta_f ID_{jlt} + \beta_X X_{jmlt}}_{V_{jmlt}} + \epsilon_{jmlt}$$

The platform then ranks products based on the realization of this value, with the highest value ranked first. The probability that product j is ranked before products $\{1, ..., k\} \subset J$ is:

$$Pr(V_{jmlt} > \max\{V_{1mlt}, ...V_{kmlt}\}) = \frac{\exp(V_{jmlt})}{\exp(V_{jmlt}) + \sum_{i=1}^{k} \exp(V_{imlt})} \tag{6}$$

The probability of observing a specific ranking can be written as the product of such terms, representing a sequential process in which the platform selects the most preferred alternative, then the most preferred alternative among the remaining products, and so on.

[5] An alternative approach assumes the platform uses a linear ranking algorithm. I conduct a robustness test under that assumption and present the results in the online Appendix II.

5 Identification and Estimation

5.1 Demand Side

5.1.1 Product and Platform Utilities

The product mean utilities δ_{jlt} are identified from observed market shares, where a version of the Berry (1994) and the Berry et al. (2013) inversion theorem applies to equation (2). For the platform utilities, we have:

$$\delta_l - b_{lt} + E[\max_j\{\delta_{jlt} + \epsilon_{ijt}\}|l] = \ln(s_{mlt}) - \ln(s_{m0t}) \tag{7}$$

This allows for identification of δ_l by recovering the expected maximum utility from the logit formula and subtracting it from the left-hand side of equation (7).

5.1.2 Search Frictions and Endogeneity

The key primitives to estimate for each market m are consumers' search frictions, captured by $\lambda_{nml} \sim \exp(\beta_{ml})$, and consumers' price sensitivity α_{ml}. Estimating the causal effect of a product's rank on its sales faces an endogeneity problem: the unobserved demand shock ξ_{jlt} in equation (2) may be correlated with the product's rank r_{jlt}, as platforms likely rank products with higher unobserved quality more favorably.

To address this endogeneity, I follow Yu (2024) and assume that the unobserved demand shock ξ_{jlt} follows a first-order autoregressive process:

$$\xi_{jlt} = \rho_{ml}\xi_{jl,t-1} + \eta_{jlt}, \quad \eta_{jlt} \sim \text{i.i.d}, \quad \mathbb{E}(\eta_{jlt}) = 0, \quad \eta_{jlt} \perp \xi_{jl,t-1} \tag{8}$$

The identification strategy relies on two key assumptions:

$$r_{jl,t-1} \perp \eta_{jlt} \tag{9}$$

$$\text{Corr}(r_{jl,t-1}, r_{jlt}|\xi_{jlt}) \neq 0 \tag{10}$$

Assumption (9) states that when the platform determines a product's rank, it does not anticipate future demand innovations. Assumption (10) requires that the platform's ranking algorithm considers sales performance over an extended period, not just current sales. Under these assumptions, lagged rank $r_{jl,t-1}$ is correlated with current rank r_{jlt} but orthogonal to the current demand innovation η_{jlt}, providing a valid instrument for identifying the causal effect of rank on sales.

The intuition for identification is as follows. Consider first a product with constant rank over time: fluctuations in its sales reveal the persistence of demand shocks, identifying ρ_{ml}. Now consider products with the same current demand shock ξ_{jlt} but different shock histories: these products will have different current rankings due to their different lagged shocks. Since lagged ranks are orthogonal to current innovations by assumption (9), variation in lagged ranks provides exogenous variation in current ranks, identifying β_{ml}.

5.1.3 Estimation Procedure

Given these assumptions, I estimate β_{ml} and ρ_{ml} for each platform and market using the Method of Moments with the following moment conditions:

$$\mathbb{E}\begin{pmatrix} \eta_{jlt}\xi_{jl,t-1} \\ \eta_{jlt}r_{jl,t-1} \end{pmatrix} = 0 \tag{11}$$

When the panel of products is unbalanced, the moment conditions in (11) can be modified to account for new products that enter the panel or products that drop out as follows:

$$\mathbb{E}\begin{pmatrix} (\xi_{jlt} - \rho_{ml}^{t-h_{jl}}\xi_{jl,h_{jl}})\xi_{jl,h_{jl}} \\ (\xi_{jlt} - \rho_{ml}^{t-h_{jl}}\xi_{jl,h_{jl}})r_{jl,h_{jl}} \end{pmatrix} = 0 \tag{12}$$

where h_{jl} is the last period in which product j is observed on platform l before t. These conditions assume that demand innovations over the observation gap are orthogonal to information available at the last observed period, and that selection into the observed sample preserves these moments.

Call $\theta_D = (\alpha_{ml}, \gamma_{ml}, \beta_{ml}, \rho_{ml}, \delta_l)$ the vector of demand parameters that characterize the buyer side of the model. The demand estimation proceeds in the following steps for each platform and market:

1. Given β_{ml}, invert observed market shares s_{jlt} to recover mean utilities δ_{jlt} using equation (2).

2. Regress δ_{jlt} on product fixed effects, time fixed effects, fulfillment method indicators (ID_{jlt}), and price p_{jlt} to recover the preference parameters. I use a two-stage IV estimator for price and integrated delivery where the instruments are average prices and average use of integrated delivery of similar products in other markets, delivery costs by FBA and Full, and available stock of the product.

3. Calculate the residuals as the unobserved demand shocks ξ_{jlt}.

4. Given ρ_{ml}, calculate the demand innovations η_{jlt} using equation (8).

5. Search for parameters (β_{ml}, ρ_{ml}) that minimize the GMM objective function based on the moment conditions in equation (11) or (12).

6. After GMM, estimate platform mean utilities δ_l using equation (7).

Note that the identification and estimation procedure is done market by market, which can lead to biased estimates due to, for example, independent sampling errors in each market. To account for this, I employ an empirical Bayes procedure so that the market specific parameters are shrunken towards their mean value across markets. So, let $\hat{\theta}^m$ be the market-specific parameters. The empirical-Bayes posterior means are given by

$$\tilde{\theta}^m = \frac{\sigma_\theta^2}{\sigma_\theta^2 + se(\hat{\theta}^m)^2}\hat{\theta}^m + \frac{se(\hat{\theta}^m)^2}{\sigma_\theta^2 + se(\hat{\theta}^m)^2}\overline{\theta}$$

5.2 Seller Side

The next step is to estimate the marginal cost and the delivery cost of the products when shipped through a third-party delivery service based on observed product prices and integrated delivery prices. I use a two-stage method similar to Bajari et al. (2007) and Pakes et al. (2015). In the first stage, I estimate the demand parameters and assume that the seller's pricing and delivery strategy is optimal under the structural demand function. Then, any perturbation of the prices or delivery choice should yield profits no greater than those under observed choices (Saeedi, 2019). The cost parameters should satisfy the above condition and then I can estimate them by minimizing the following loss function with respect to third-party delivery prices

$$\sum_{\text{s, perturbations}} (\pi_{s,perturbed}(\hat{\theta}_D) - \pi_{s,original}(\hat{\theta}_D))^2 1[(\pi_{s,perturbed}(\hat{\theta}_D) - \pi_{s,original}(\hat{\theta}_D)) > 0] \tag{13}$$

Where $\pi_{s,perturbed}(\hat{\theta}_D)$ is the profit function of seller s under the estimated demand parameters $\hat{\theta}_D$ and perturbed prices and delivery methods, $\pi_{s,original}(\hat{\theta}_D)$ is the profit function under the original prices and delivery method. The estimation procedure is to simulate buyers' decisions under the original and perturbed policy functions to compute sellers' profits and find the cost parameters that minimize the simulated loss function.

5.3 Platform Parameters

5.3.1 Commission Rates and Delivery Prices

I recover the keyword-specific weights μ^C and μ^P that platforms assign to consumer and seller surplus using the first-order conditions of the platform's problem with respect to commission rates and delivery prices. Given observed product prices, commission rates, and delivery prices, these first-order conditions provide a system of equations that identifies the weights.

5.3.2 Ranking Algorithm Parameters

For the Rank-Ordered Logit model of rankings, I estimate the parameters β_p, β_f, and β_X using maximum likelihood based on observed rankings pooling observations across markets and periods. The ranking value function includes the following variables and their quadratic interaction terms: current prices, lagged market share, time and market fixed effects, lagged number of reviews, a dummy for positive overall reviews (greater than 4.5 stars, lagged), the delivery method of the product, and time-invariant product characteristics including brand, keyword relevance,[6] and the length of the product description.

[6]Having a lengthy title that mentions several potential keywords is a known strategy among sellers on these platforms to achieve better rankings. I create a dummy variable equal to 1 if the searched keyword is contained within the product name.

6 Estimation Results

Table 7 presents the parameter estimates of the model, and Table 8 presents the ranking-algorithm estimates.The central estimates for this paper concern integrated delivery so I organize the discussion of the results around three questions: how integrated and third-party delivery services differ, how strongly do the platforms' ranking algorithms favor integrated delivery, and how much does delivery and price competition shape outcomes on each platform.

Table 7: Parameter Estimates for Mercado Libre and Amazon

	Mercado Libre			Amazon		
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Parameter	Min	Mean	Max	Min	Mean	Max
Demand Shock Persistent Comp. (ρ)	[0.0394	0.2478	0.8136]	[0.0160	0.3248	0.8191]
Search Friction (β)	[0.0000	0.0150	0.0208]	[0.0021	0.0508	0.1567]
Consumer Price Sensitivity (α)	[-8.5146	-4.9322	-3.7662]	[-10.6503	-5.1861	-3.0021]
Full/FBA Taste (γ)	[-1.4492	0.3227	2.7388]	[-0.5720	0.4689	2.3258]
Consumer Platform Utility (δ_l)	[0.9358	0.9503	0.9569]	[0.9152	0.9390	0.9636]
Own Price Elasticity	[-2.7372	-1.4112	-0.9840]	[-8.7482	-3.8231	-1.3897]
Markup	[0.2356	0.3712	0.8253]	[0.2341	0.3975	0.8123]
Full/FBA Delivery Cost ($MXN)	[68.99	229.60	386.43]	[60.47	207.44	582.08]
Third Party Delivery Cost ($MXN)	[20.02	124.91	365.49]	[42.31	105.98	387.07]
Platform Seller Weight (μ_l^P)	[0.0305	0.5701	2.0173]	[0.0094	1.0377	9.2838]
Platform Consumer Weight (μ_l^C)	[0.0127	1.2033	14.3871]	[0.0023	0.3378	2.9456]

Notes: The table shows the mean parameter estimate and the range of the estimates across 50 keywords analyzed tracked over 24 months (May 2023–May 2025). The full results of the estimation, along with standard errors for all markets are in Table 11 in the Appendix.

On the first question, how integrated and third-party delivery services differ? The estimates show that consumers value the integrated delivery: the taste parameter γ_{ml} is positive on average on both platforms, and larger on Amazon (0.46) than on Mercado Libre (0.32), so FBA and Full and are both perceived to be higher quality than third-party alternatives. Figure 2a shows the distribution of willingness to pay for the integrated delivery as a percentage of the item's price. Consumers on Amazon are willing to pay 26% more for a product on average if it is delivered by FBA. Similarly, consumers on Mercado Libre are willing to pay around 25% extra on average for a product delivered by Full. Notice however that these averages hide some heterogeneity, with estimates ranging from -25% to 75% on Amazon and -50% to 125% on Mercado Libre.

FBA and Full, however, are costly to provide for sellers: integrated delivery costs 84-95% more on average than third-party alternatives ($208-230 MXN versus $105-125 MXN, Table 7). Figure 2b shows the delivery cost as a fraction of the item's final price for products delivered by Full, FBA and third-parties. The average cost ratio when using third party delivery is around 16% while Full is 21% and FBA closer to 30%. The results indicate that both platforms have considerable market power in the delivery segment they intermediate.

To understand why sellers would adopt the integrated delivery despite the increase in cost we need to note that both platforms exhibit substantial search frictions. Figure

Table 8: Ranking Algorithm Parameter Estimates

	Mercado Libre		Amazon	
Variable	Coef.	SE	Coef.	SE
Price & Delivery:				
Log(Price)	0.061*	(0.033)	0.021*	(0.010)
Full/FBA Delivery	0.660**	(0.293)	0.712***	(0.262)
Log(Price) × Full/FBA	−0.054	(0.038)	0.112***	(0.037)
Product Performance:				
Relevance Dummy	0.042	(0.075)	0.384***	(0.055)
Log(Monthly Sales$_{t-1}$)	0.164***	(0.015)	0.460***	(0.026)
Good Reviews$_{t-1}$ (>4.5)	0.348***	(0.089)	0.481***	(0.037)
Number of Reviews$_{t-1}$	−0.064*	(0.034)	0.130***	(0.035)
Keyword Fixed Effects	Yes		Yes	
Time Fixed Effects	Yes		Yes	
Observations	50,050		54,050	
Log-Likelihood	−29,439		−39,676	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is product rank within search results, estimated using the Rank-Ordered Logit (ROL) model described in Section 5.3.2. All regressions include keyword fixed effects. Standard errors are clustered at the keyword level. Estimated on 50 keywords analyzed tracked over 24 months (May 2023–May 2025).

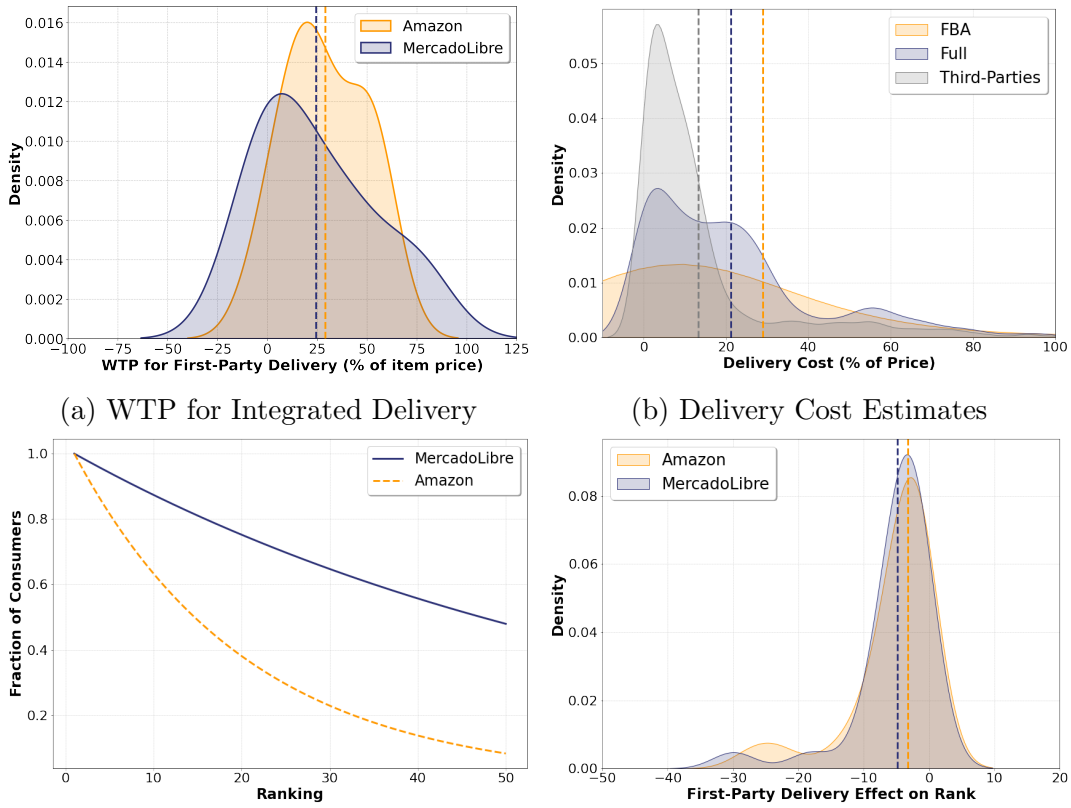
2c shows that 62% of Amazon consumers consider only the first 20 products, the median consumer examines only the top 15 products, 22% of Mercado Libre consumers stop searching within the first 20 products and a median search depth is around 50 products. So, sellers would adopt Full or FBA if it leads to higher visibility, and therefore higher sales, on the platform.

So, how strongly do the platform's ranking algorithms favor their integrated delivery services? The Rank-Ordered Logit (ROL) model of platform rankings is reported in Table 8, a positive coefficient implies a desirable characteristic for the platforms when ranking the products.[7] The results show that, controlling for price, past sales, and reviews, products using Full or FBA receive a higher ranking value on both platforms. Figure 2d translates the positive coefficients in Table 8 into ranking positions: Full delivery moves a product up 6 positions on Mercado Libre, and FBA moves a product up 4 positions on Amazon, on average relative to an otherwise identical product using third-party delivery, with an advantage of up to 30 to 40 positions in some markets.

The ROL model of platform rankings also implies that on both platforms higher sales, better reviews and, importantly, a higher price than similar alternatives gives sellers a higher probability of being shown in better rankings.[8] Since demand is price elastic on both platforms (somewhat more so on Amazon where the mean own-price elasticity is −3.82 versus −1.41 on Mercado Libre), this is evidence that both platforms want to show products that maximize their revenue, as opposed to consumer surplus. Sellers on both platforms have two incentives to increase prices: better rankings and more revenue per sale, and an incentive to decrease prices to get more sales conditional on consumers seeing their product. So, the algorithms simultaneously reduce the visi-

[7]The model fits the data relatively well, in Figure 10 in the Appendix, I show the observed and predicted probability each ranking.

[8]Figures 11 and 12 show the estimated rank effect of using FBA/Full and decreasing the price of an item by 1% in the top 25 keywords my sales.



(a) WTP for Integrated Delivery

(b) Delivery Cost Estimates

(c) Search frictions

(d) Effect of ID on Ranking

Figure 2: Estimation Results

Note: Panel (a) shows the kernel density of consumers' willingness to pay for integrated delivery, expressed as a percentage of the item's price, recovered from the estimated taste parameter γ_{ml} divided by the price sensitivity α_{ml} for each platform and keyword. Panel (b) shows the kernel density of the estimated delivery cost as a percentage of the item's price, separately for products delivered by FBA, Full, and third-party providers. Panel (c) shows the estimated fraction of consumers who examine at least the first n products for each platform. Panel (d) shows the kernel density of the estimated effect of using integrated delivery on ranking position, relative to an otherwise identical product using third-party delivery. Dashed vertical lines indicate the cross-market mean. Estimates are based on 50 keyword markets tracked over 24 months (May 2023–May 2025).

bility of third-party delivery and of cheaper product alternatives.

So, how much does delivery and price competition shape outcomes on each platform? The estimates of how much Amazon and Mercado Libre favor their integrated delivery are small relative to other estimates found in the literature and that search frictions, especially on Mercado Libre, are also somewhat small. However, consumer price sensitivity is larger than studies that focus on the US, consistent with consumers in Mexico having lower income, and there are large differences in cost of providing the integrated delivery services compared to third-parties. Therefore, the main harm to consumers from vertical integration in this setting comes from the increased costs of integrated delivery and not the matching distortions as in earlier self-preferencing papers (Farronato et al. (2023), Chen and Tsai (2024), Yu (2024)).

Finally, the two platforms differ not only in how they rank products, but in how they weigh the parties on each side of the market. The platform-consumer and platform-seller weights recovered from the first-order conditions (Table 7, rows 10-11) show that

Amazon assigns a higher weight to seller surplus than Mercado Libre does. Combined with the ranking-position asymmetry documented above, this suggests Mercado Libre's algorithm currently extracts more surplus through delivery-based ranking distortions than Amazon's does. This asymmetry is the basis for the counterfactual comparisons in Section 7: because the platforms do not start from the same degree of ranking bias, a common regulatory standard should be expected to affect them differently.

7 Counterfactual Exercises

I conduct two sets of counterfactual exercises. The first asks what happens if both platforms are barred from favoring products that use their own integrated delivery service in rankings. I present the resulting welfare and market-outcome changes through three progressively less restrictive equilibrium concepts, moving from a pure re-ranking exercise to a full equilibrium in which both sellers and platforms reoptimize. The second counterfactual asks what happens if Mercado Libre's integrated delivery service is separated from the platform while Amazon's ranking algorithm and vertical relation with delivery is left untouched. This counterfactual allows me to examine what is the effect of platform competition on self-preferencing and on the market power of the platforms on the delivery market.

7.1 Unbiased Ranking

I conduct a counterfactual exercise to assess an intervention on the platforms' ranking algorithms aimed at reducing their market power in the delivery segment. In the counterfactual, platforms cannot favor products using their integrated delivery services, which I implement by setting the coefficients on Full/FBA delivery to zero in the Rank-Ordered Logit ranking model (Table 8). The ranking algorithms can still favor higher prices, so price competition under this intervention is softer than it would be under a benchmark in which products are ranked purely by expected consumer utility; I report that benchmark, together with a random-ranking and a no-search-friction benchmark, in the online Appendix III. Under the unbiased-ranking intervention, sellers have weaker incentives to adopt platform-integrated delivery, since doing so no longer buys additional visibility; the only remaining reason to adopt it is its higher quality relative to third-party alternatives.

I report results under three equilibrium concepts that isolate the matching, pricing, and platform-fee margins of the intervention. The first, the *matching effect*, is a partial-equilibrium exercise in which seller prices and delivery choices are held fixed at their baseline values, so that welfare changes arise purely from consumers facing a different, unbiased ordering of the same choice set. The second, the *seller equilibrium*, allows sellers to reoptimize prices and delivery method given the new ranking rule, holding platform commission and delivery fees fixed at baseline. I recover a simulated equilibrium: I simulate the ranking distribution implied by the new algorithm and allow one seller at a time to set its profit-maximizing price, holding all other sellers fixed, then iterate across sellers and update platform market shares until both prices and market shares converge. The third, the *platform equilibrium*, additionally allows platforms to

respond to the intervention by adjusting the commission rate paid by sellers; since platforms can no longer charge indirectly for visibility through delivery fees, they may raise commissions on all products uniformly to recoup part of the lost rent. The first two equilibrium concepts assume that the platforms do not respond to the interventions. However, platforms might respond to the new rankings by adjusting other parts of their business, which could dampen the intended effects of the policy so the final counterfactual should be read as the policy relevant exercise.

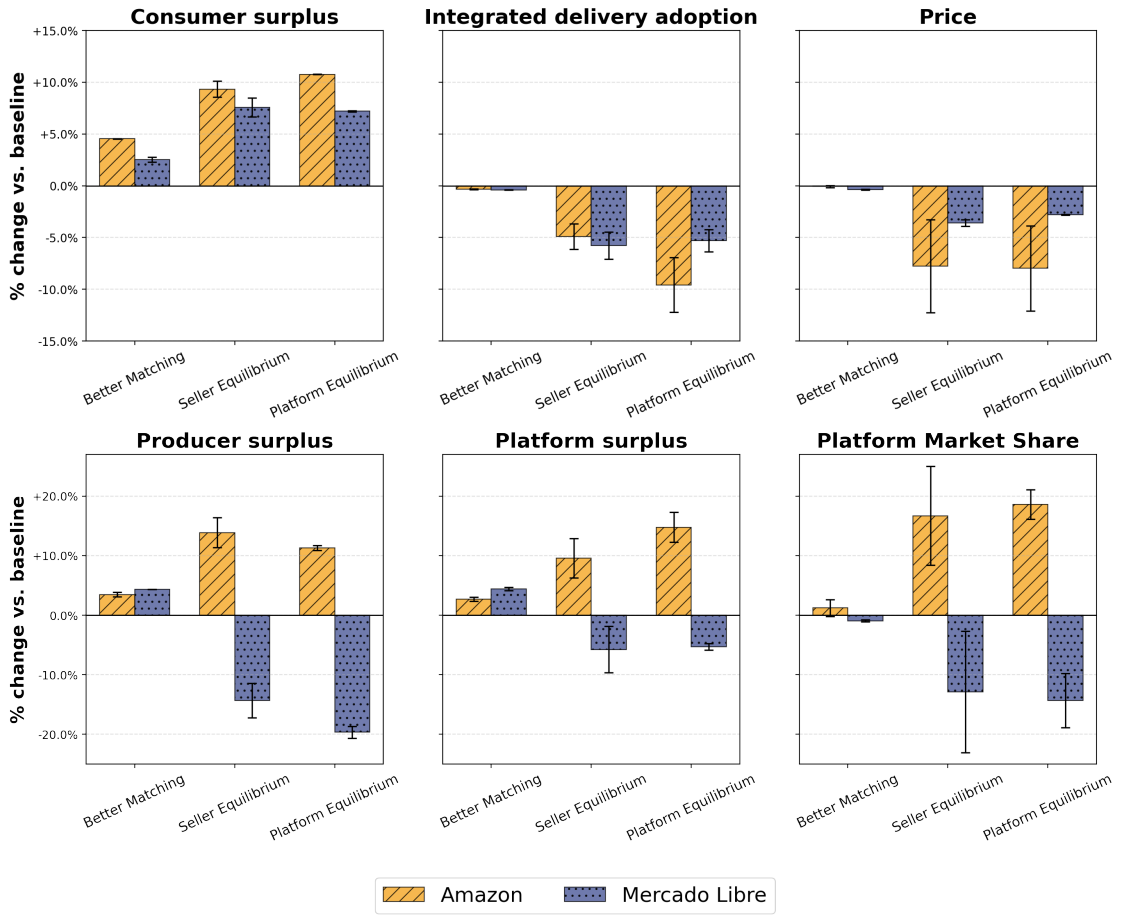


Figure 3: Welfare and Market Outcomes Across all Counterfactuals

Notes: This Figure presents the percentage change of different welfare measures in three equilibrium counterfactual scenarios - Better Matching, Seller Equilibrium, and Platform Equilibrium - compared to the baseline equilibrium. The changes are measured using average per-transaction surplus. Total surplus is the sum of consumer, producer, and platform surplus across both platforms, weighted by market size and market share. Analysis based on 50 Amazon and Mercado Libre keywords.

Figure 3 plots the percentage change in market outcomes across the three equilibrium concepts of the counterfactual relative to the baseline, Table 12 in the Appendix reports the corresponding levels and percentage changes for each panel. Total surplus does not move monotonically across the three equilibria: it rises 3.61% under the *matching effect*, then rises to 4.56% in the *seller equilibrium*, and then falls to 3.71% in the *platform equilibrium*. This pattern arises because the *matching effect* holds prices and delivery choices fixed at values that were optimal under the old, biased ranking, so its 3.61% figure isolates the pure gain from consumers facing a better choice set,

holding seller choices fixed at baseline. Once sellers actually reoptimize prices and delivery method in response to the new ranking rule, the resulting price and delivery adjustments increase this matching gain, and platforms' subsequent fee response claws back only part of the difference. The *platform equilibrium*, not the *matching effect* or the *seller equilibrium*, is therefore the relevant welfare benchmark for evaluating the intervention in equilibrium.

Consumer surplus rises on both platforms under every equilibrium concept, but by increasingly different amounts. Under the *matching effect*, consumer surplus rises 4.53% on Amazon versus 2.53% on Mercado Libre, consistent with Amazon consumers facing higher baseline search frictions and therefore benefiting more from a less distorted ranking. These small consumer surplus gains are also consistent with the relatively small degree of self-preferencing by the platforms. The gap widens in the *seller equilibrium*: consumer surplus rises to 9.33% on Amazon versus 7.56% on Mercado Libre, tracking the platforms' price declines (Panel (c)), which reach −7.76% on Amazon against −3.59% on Mercado Libre, alongside similar-sized drops in integrated delivery adoption on both platforms (Panel (b): −5.04% on Amazon, −5.77% on Mercado Libre) as sellers move away from more expensive integrated delivery. In the *platform equilibrium*, as Mercado Libre raises its commission rate by nearly 17% to recoup lost delivery rents, its consumer surplus gain falls back from 7.56% to 7.20%, while Amazon's consumer surplus continues to rise, reaching 10.76%.

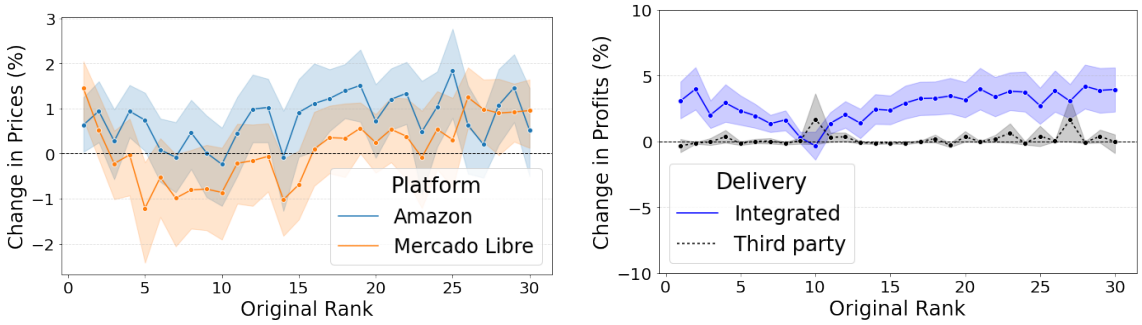


Figure 4: Prices and Profit Changes by Baseline Ranking.
Note: The Figure shows the percentage change in prices and profits under the platform equilibrium counterfactual, plotted against each product's baseline (pre-intervention) ranking position. The left panel shows the average price change by platform. The right panel shows the average profit change by delivery method, pooling both platforms. Shaded regions indicate 95% confidence intervals.

Amazon's producer surplus, platform surplus, and consumer market share all rise steadily across the three equilibrium concepts (Panels (d)–(f)), reaching +11.30%, +14.77%, and +18.60% above baseline, respectively, in the platform equilibrium. Mercado Libre moves in the opposite direction on all three margins: producer surplus falls 14.35% in the *seller equilibrium* and 19.64% in the *platform equilibrium*, Mercado Libre's surplus falls by up to 6.21%, and its consumer market share falls by up to 14.34%. This is the same mechanism discussed in Section 6: because Mercado Libre's baseline algorithm favors Full more aggressively than Amazon's favors FBA, it must reorder its results more substantially once both platforms are held to a common ranking standard, and this larger reordering costs it market share and rents that migrate toward the less-biased platform. A regulatory change that looks neutral, since it applies the same rule to

both platforms, therefore has real distributional consequences for platform competition.

Figure 4 documents how these aggregate patterns are distributed across products, using each product's baseline (pre-intervention) rank. On both platforms, price declines are concentrated among products on the top ranks while products on lower rank positions increase their prices on average (left panel). Profit gains are concentrated among sellers who originally used integrated delivery across all ranking positions (right panel). This is consistent with the mechanism above: integrated-delivery sellers capture a disproportionate share of the producer-surplus gains precisely because they no longer have to overpay for visibility through the ranking algorithm, while third-party sellers see comparatively little change.

As discussed in the introduction, two modeling assumptions matter for interpreting these results. First, consumers and sellers single-home in all counterfactuals. If some consumers compare products across Amazon and Mercado Libre, they can partly avoid the effects of ranking bias on either platform, so the consumer surplus gains reported in Table 12 and Figure 4 should be read as an upper bound. Second, the set of sellers and products on each platform is fixed. Under unbiased or utility-based ranking, sellers using third-party delivery become more visible, which could attract entry and push prices down further than the model predicts. If platforms instead respond to the regulation by raising commission rates, some sellers may exit and reduce the options available to consumers. The net effect of seller entry and exit on the welfare estimates is therefore ambiguous.

7.2 Mercado Libre Divestiture

The unbiased-ranking exercise in Section 7.1 regulates both platforms' algorithms directly. Here I ask a different question: how much of the market power documented in Section 6 is disciplined by competition between Amazon and Mercado Libre, rather than by the design of either platform's own algorithm? To answer this, I consider a counterfactual in which Mercado Libre's Full service is separated from the platform: I set delivery prices equal to third-party delivery prices and remove any ranking advantage from using Full, while leaving Amazon's ranking algorithm and FBA service completely unchanged. I allow the platforms to re-optimize their commission fees and the sellers on each platform to re-optimize their prices and delivery methods. This exercise is not intended as a realistic regulatory proposal; no authority has proposed divesting a specific rival's delivery arm. Rather, it approximates what would happen to market outcomes, and to Amazon's own consumers in particular, if Amazon's self-preferencing incentives were no longer disciplined by a rival offering a less-biased alternative, that is, if Amazon's effective market power in Mexico approached that of a monopolist in this segment. Sellers and consumers and both platforms are allowed to respond in equilibrium. Figure 5 reports the percent changes of different welfare measures under the divestiture counterfactual compared to the baseline.[9]

[9]Table 13 in the Appendix reports the results along with standard errors computed using the bootstrap method.

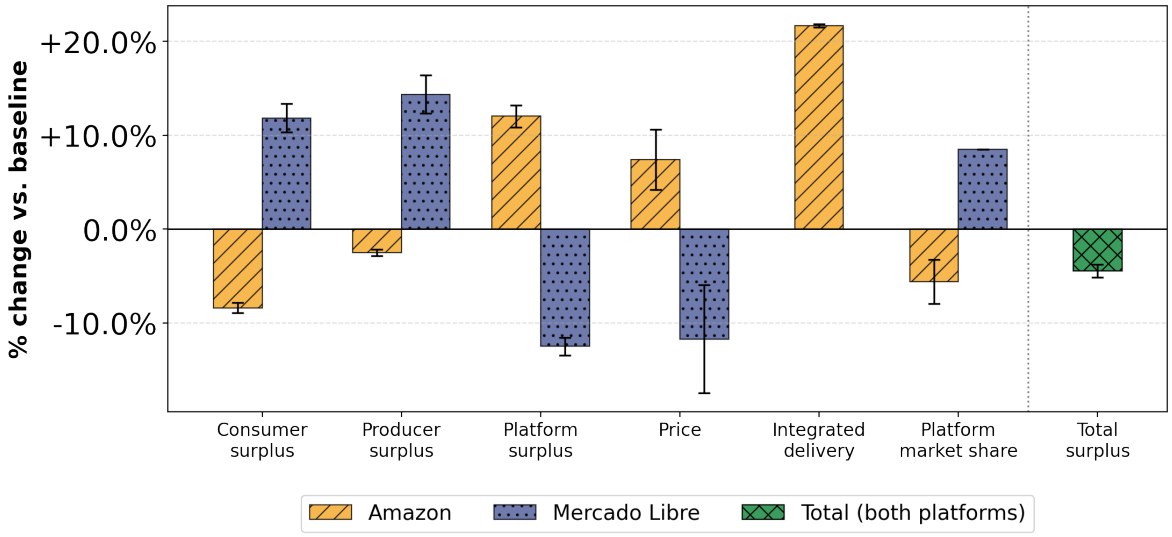


Figure 5: Welfare and Market Outcomes for the Divestiture Counterfactual

Notes: This Figure presents the welfare effects of the divestiture of Full compared to the baseline. Consumer surplus, producer surplus, platform surplus, and total surplus are measured in MXN. ID (%) represents the integrated delivery adoption rate. Total surplus is the sum of consumer, producer, and platform surplus across both platforms, weighted by platform market shares. Analysis based on 50 keywords.

Mercado Libre's own consumers benefit substantially from losing Full: with delivery repriced at third-party rates, consumer surplus on Mercado Libre rises by 11.82% as its average price falls by 11.71%. Producer surplus on Mercado Libre also rises by 14.36% since sellers save on delivery. This gain comes almost entirely at the platform's own expense. Mercado Libre's surplus falls sharply by 12.51%, even after Mercado Libre raises its commission rate by nearly 15%, and its consumer market share rises by 8.48%.

Amazon, meanwhile, gains profits but loses market share. Its market share decreases by 5.60%, and its surplus rises by 12.02% as they collect higher fees (12.94% higher than the baseline, on average) from products with higher prices, up 7.40% compared to the baseline, and sellers' use of *FBA* increases by 21.68%. Consumer surplus on Amazon, however, *falls* by 8.40%, even though FBA prices and quality are held fixed throughout this exercise. With its principal competitor's constraint removed, Amazon behaves closer to an unconstrained incumbent, and its own consumers bear the cost.

Total surplus falls by 4.47%, once Mercado Libre's competitive discipline on Amazon is removed. Unlike the unbiased-ranking exercise in Section 7.1, where regulating ranking bias directly *raises* total surplus, this decline is driven by weaker competition. This 4.47% figure is therefore a useful, if partial, estimate of the value of platform competition in this market, distinct from and additional to the direct value of regulating algorithmic bias documented above. In this exercise the divestiture of Mercado Libre and Full stops disciplining Amazon's incentive to favor its own delivery service and harms consumers.

Taken together, these results have two implications for competition policy. First, both Amazon and Mercado Libre currently place excessive weight on promoting their own delivery services through rankings: requiring both platforms to rank products

without regard to delivery method raises total surplus by 3.71% in the full platform equilibrium, lowers prices, and raises producer surplus. Second, direct algorithmic-bias regulation is not the only lever available, nor necessarily the largest: the divestiture exercise suggests that the mere presence of a competing platform disciplines self-preferencing even absent any change to ranking rules, and that weakening this competitive channel costs total surplus, and Amazon's own consumers specifically, on a scale comparable to the direct effect of algorithmic bias documented above. This suggests that competition authorities evaluating remedies in two-sided markets should weigh not only how a given platform ranks products, but how much a rival's presence, or absence, already constrains that ranking in equilibrium.

8 Conclusion

This paper examines how retail platforms tie the visibility they control through ranking algorithms to sellers' purchase of the platform's own delivery service, and quantifies the resulting welfare effects in Mexico's online marketplace. Using novel panel data of search results from Amazon and Mercado Libre over two years, I develop and estimate a structural model that incorporates consumer search behavior, platform ranking algorithms, and seller strategic decisions. Platform-delivery integration affects market outcomes through two distinct channels: efficiency gains from improved service quality and market power effects through algorithmic bias in product rankings.

The empirical evidence shows substantial search frictions on both platforms. On Amazon, 62% of consumers consider only the first 20 products and the median consumer examines only the top 15 products, while on Mercado Libre 22% stop searching within the first 20 products and the median search depth is around 50 products. These frictions make ranking position valuable. Consumers value integrated delivery, they are willing to pay about 26% more for FBA on Amazon and 25% more for Full on Mercado Libre. Yet the integrated services are about 84-95% more expensive than third-party delivery, and the ranking algorithms systematically favor them beyond these quality differences.

In a counterfactual exercise, platforms are barred from conditioning rankings on the use of integrated delivery. Under the regulation, total surplus rises by 3.71% even after the platforms respond by raising their commission fees by 14-17%. Integrated delivery adoption falls by 9.05% on Amazon and 5.30% on Mercado Libre, while prices fall by 7.99% and 2.80%, respectively. Consumer surplus rises by 10.76% on Amazon and 7.20% on Mercado Libre. The intervention also reallocates consumers across platforms: Amazon's consumer market share rises by 18.60%, while Mercado Libre's falls by 14.34%. Mercado Libre responds to the loss of delivery rents by raising its commission rate, which reduces part of the consumer gain. Because Mercado Libre begins with the more delivery-biased ranking algorithm, the same regulatory standard requires a larger adjustment on Mercado Libre and shifts consumers and rents toward Amazon. A neutral ranking rule can therefore have large distributional consequences across competing platforms.

A second counterfactual shows that platform competition is itself an important constraint on self-preferencing. I separate Mercado Libre's Full service from the platform while leaving Amazon's ranking algorithm and FBA service unchanged. Mercado Libre consumers benefit from the lower delivery cost, with consumer surplus increasing by 11.82% and Mercado Libre winning 8.48% consumer market share. Amazon loses market share, but makes higher profits. Consumer surplus on Amazon falls by 8.40%. Total surplus falls by 4.47%. Thus, removing Mercado Libre's competitive discipline allows Amazon to exercise more market power even though Amazon's own delivery technology and ranking rule are not directly changed. The magnitude of this welfare loss is comparable to the direct welfare gain from eliminating delivery-based ranking bias, showing that both direct regulation and competition are quantitatively important policy margins.

Several limitations point to directions for future research. First, the full-equilibrium counterfactual lets platforms reoptimize commission rates but holds integrated-delivery prices and subscription fees fixed. A richer analysis would let platforms adjust these instruments jointly, although studying subscription fees would require more consumer-side data. Second, I treat search frictions and the platforms' remaining ranking weights as fixed. Better rankings may reduce consumers' incentive to search beyond the top results, and platforms may reweight other ranking inputs after an intervention. Modeling either response would require individual-level search data or additional assumptions on platform behavior. Finally, the Mercado Libre separation exercise isolates the competitive mechanism rather than modeling an actual divestiture. Evaluating structural remedies directly would require incorporating entry and sellers' platform choices.

Despite these limitations, the results provide evidence that platform-delivery integration distorts search rankings, affecting both within-platform efficiency and competition between platforms. Ranking algorithms let platforms tie sellers' visibility to the purchase of a complementary service, but how profitably they can do so depends on the alternatives available to consumers and sellers.

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A Additional Tables and Figures

Table 9: Search Keywords: Category and Sample Coverage

Keyword	Category	Market size	% of total
pantalla 32 pulgadas	Electronics	1,198,956	9.47%
bocina alexa	Electronics	1,164,073	9.19%
audifonos con cable	Electronics	1,053,488	8.32%
smart watch	Electronics/Wearables	863,415	6.82%
ipad	Electronics	837,625	6.61%
mouse inalambrico	Electronics	735,778	5.81%
audifonos	Electronics	731,672	5.78%
teclado pc	Electronics	720,532	5.69%
luces led	Home & Electronics	660,173	5.21%
aire acondicionado	Home Appliances	509,525	4.02%
tenis de mujer	Footwear	475,395	3.75%
control xbox one	Electronics	343,744	2.71%
horno microondas	Home Appliances	340,000	2.68%
laptop	Electronics	311,140	2.46%
reloj hombre	Accessories	285,034	2.25%
barra de sonido	Electronics	261,740	2.07%
ring camara	Electronics	258,323	2.04%
mesa comedor	Home & Furniture	209,581	1.65%
mesa jardin	Home & Furniture	203,030	1.60%
banda ejercicio	Sports & Fitness	163,215	1.29%
pants de mujer	Apparel	136,582	1.08%
shorts de mujer	Apparel	112,145	0.89%
kit camaras	Electronics	106,372	0.84%
motos hot wheels	Toys	105,622	0.83%
colchon	Home & Furniture	102,484	0.81%
proyector	Electronics	94,908	0.75%
smart tv	Electronics	92,208	0.73%
notebook	Electronics	88,558	0.70%
lamina marmol pvc	Home Improvement	62,775	0.50%
cajas de carton	Home & Packaging	61,130	0.48%
hielera	Home & Outdoor	60,516	0.48%
minisplit inverter	Home Appliances	59,766	0.47%
poco m7	Electronics	37,427	0.30%
andadera	Baby & Kids	30,229	0.24%
arnes electrico moto	Automotive	20,549	0.16%
mens pants	Apparel	18,394	0.15%
oppo	Electronics	18,024	0.14%
huawei p7	Electronics	17,299	0.14%
paneles decorativos	Home Improvement	17,181	0.14%
gym shark	Apparel/Sportswear	16,667	0.13%
levis 513	Apparel	16,600	0.13%
chamarras hombre	Apparel	16,100	0.13%
tenis blancos	Footwear	14,981	0.12%
iphone 13 reacondicionado	Electronics	9,378	0.07%
carburador tbi	Automotive	9,128	0.07%
redmi note 12 pro plus	Electronics	4,730	0.04%
asus rog phone 9 pro	Electronics	4,346	0.03%
esquinero para baño	Home & Furniture	3,092	0.02%
mueble bano	Home & Furniture	2,842	0.02%

Notes: Market size is the combined observed sales on Amazon and Mercado Libre. The % of total is each keyword's share of the total market size across the keywords included in the sample.

Table 10: Descriptive Statistics of the Restricted Sample

	Mercado Libre		**Amazon**	
Variable	Mean	(Std. Dev.)	Mean	(Std. Dev.)
Market Structure:				
Products per Keyword	45.19	(7.52)	45.37	(3.29)
Sellers per Keyword	37.56	(17.36)	32.37	(33.29)
Product Characteristics:				
Price (MXN)	3544.32	(4624.90)	2580.89	(4584.86)
Monthly Sales (units)	342.88	(431.28)	128.6	(298.1)
Number of Reviews	950.43	(1,425.12)	452.39	(2023.67)
Rating (1-5 stars)	4.66	(0.3)	4.23	(0.79)
Commission Rate	15.03%	(4.90)	13.07%	(2.77)
First-Party Delivery (%)	61.14%	(48.74)	53.17%	(49.96)
FBA/Full Delivery Cost	149.36	(167.37)	160.28	(133.67)
Full Product Stock	28.35	(20.23)	-	-
Observations	50,050		54,050	

Notes: Sample covers 104,100 observations from 4,069 unique seller-product pairs across 50 search keywords tracked over 24 months (May 2023-May 2025), aggregated at the monthly level. Standard deviations in parentheses. Products denotes unique product listings per keyword-month. Sellers counts distinct seller identities offering products within each keyword. Monthly Sales represents average monthly unit sales as reported by platforms. First-Party Delivery refers to Full (Mercado Libre) and FBA (Amazon). All statistics computed at the product-month level.

Table 11: Demand parameter estimates by keyword and platform (all markets)

Keyword	Platform	N	ρ	β	Price sens. α	ID sens. γ
aire acondicionado	Amazon	40	0.318 (1.507)	0.000 (0.000)	-0.229 (0.204)	0.081*** (0.012)
aire acondicionado	Mercado Libre	40	0.646 (1.294)	0.000** (0.000)	-0.236** (0.110)	0.016*** (0.005)
andadera	Amazon	40	0.305 (1.786)	0.000*** (0.000)	-1.068*** (0.334)	0.036 (0.034)
andadera	Mercado Libre	40	0.000 (1.166)	0.010*** (0.001)	-4.259*** (0.494)	0.138*** (0.037)
arnes electrico moto	Amazon	30	0.174 (1.295)	0.010*** (0.000)	-1.248 (0.776)	-0.413*** (0.082)
arnes electrico moto	Mercado Libre	30	0.662 (1.515)	0.000 (0.001)	-1.714*** (0.547)	-0.026 (0.024)
asus rog phone 9 pro	Amazon	40	0.000 (0.574)	0.000** (0.000)	-5.253* (2.711)	-0.612*** (0.226)
asus rog phone 9 pro	Mercado Libre	40	0.170*** (0.000)	0.010*** (0.000)	-0.192*** (0.037)	0.441*** (0.083)
audifonos	Amazon	40	0.122 (0.483)	0.012*** (0.000)	-3.210*** (0.875)	0.017 (0.075)
audifonos	Mercado Libre	40	0.000 (0.069)	0.000** (0.000)	-0.156 (0.118)	2.211*** (0.324)
audifonos con cable	Amazon	30	0.000 (0.707)	0.031*** (0.001)	-2.863*** (0.665)	0.393*** (0.058)
audifonos con cable	Mercado Libre	30	0.657 (1.044)	0.009*** (0.000)	-0.356 (0.309)	1.238 (0.842)
banda ejercicio	Amazon	30	0.256 (0.387)	0.017*** (0.000)	-0.236 (0.290)	0.059 (0.042)
banda ejercicio	Mercado Libre	30	0.141 (1.017)	0.009*** (0.001)	-4.247*** (0.564)	0.931*** (0.088)
barra de sonido	Amazon	35	0.289 (0.881)	0.009*** (0.000)	-5.924*** (1.724)	1.185*** (0.269)
barra de sonido	Mercado Libre	35	0.647*** (0.026)	0.000*** (0.000)	-2.038*** (0.590)	-0.166*** (0.062)
bocina alexa	Amazon	40	0.329 (1.396)	0.000*** (0.000)	-0.091 (0.671)	0.097 (0.088)
bocina alexa	Mercado Libre	40	0.743*** (0.117)	0.000*** (0.000)	-2.837*** (0.855)	0.284*** (0.085)
cajas de carton	Amazon	40	0.175 (0.972)	0.000 (0.000)	-2.669*** (0.776)	0.070*** (0.010)
cajas de carton	Mercado Libre	40	0.521 (2.633)	0.001*** (0.000)	-0.668** (0.312)	-0.049*** (0.010)
carburador tbi	Amazon	35	0.207 (0.617)	0.000 (0.000)	-0.979** (0.437)	-0.098* (0.053)
carburador tbi	Mercado Libre	30	0.116 (0.715)	0.000 (0.002)	-10.783*** (2.545)	1.583*** (0.238)
chamarras hombre	Amazon	35	0.259 (1.431)	0.000*** (0.000)	-1.115*** (0.355)	-0.031 (0.035)
chamarras hombre	Mercado Libre	35	0.184 (0.827)	0.007*** (0.001)	-4.109*** (0.538)	0.879*** (0.083)
colchon	Amazon	30	0.465 (0.969)	0.010*** (0.003)	-0.653** (0.263)	0.175*** (0.023)
colchon	Mercado Libre	30	0.684 (0.525)	0.007*** (0.000)	-0.590*** (0.201)	0.108*** (0.020)
control xbox one	Amazon	40	0.000 (0.355)	0.000 (0.001)	-0.519 (0.823)	0.110*** (0.038)
control xbox one	Mercado Libre	40	0.475 (0.999)	0.000*** (0.000)	-0.834** (0.336)	-0.025*** (0.008)
disco duro solido	Amazon	30	0.169 (0.853)	0.010*** (0.001)	-4.723*** (1.204)	0.558*** (0.154)
disco duro solido	Mercado Libre	30	1.000 (1.667)	0.000*** (0.000)	-0.102 (0.535)	0.172** (0.070)
esquinero para baño	Amazon	40	0.499 (3.513)	0.001*** (0.000)	-0.450 (0.939)	-0.046 (0.028)
esquinero para baño	Mercado Libre	40	0.155*** (0.002)	0.011*** (0.000)	-2.916*** (0.158)	0.574*** (0.131)
gym shark	Amazon	40	0.000 (0.145)	0.000*** (0.000)	-0.189*** (0.049)	0.011** (0.005)
gym shark	Mercado Libre	40	0.507 (1.613)	0.000*** (0.000)	-2.333*** (0.366)	0.028 (0.022)
hielera	Amazon	35	0.000 (0.072)	0.000 (0.000)	-0.663*** (0.159)	1.025*** (0.089)
hielera	Mercado Libre	35	0.302 (1.987)	0.002*** (0.000)	-0.752** (0.306)	0.051*** (0.011)

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Table 11 – continued from previous page

Keyword	Platform	N	ρ	β	Price sens.	ID sens.
horno microondas	Amazon	30	0.140 (0.683)	0.010*** (0.000)	-7.046*** (0.961)	0.019 (0.178)
horno microondas	Mercado Libre	40	0.292 (0.352)	0.002*** (0.000)	-0.070 (0.176)	0.232*** (0.073)
huawei p7	Amazon	35	0.002 (0.585)	0.009*** (0.000)	-2.438* (1.424)	0.243*** (0.080)
huawei p7	Mercado Libre	35	0.495 (2.607)	0.009*** (0.001)	-8.280*** (0.958)	0.546*** (0.053)
ipad	Amazon	40	0.152 (0.513)	0.005*** (0.000)	-1.608 (1.472)	0.006 (0.035)
ipad	Mercado Libre	40	0.142 (0.283)	0.000*** (0.000)	-0.273*** (0.080)	0.028*** (0.010)
iphone 13 reacondicionado	Amazon	40	0.209 (1.061)	0.000*** (0.000)	-0.924** (0.362)	-0.094** (0.044)
iphone 13 reacondicionado	Mercado Libre	40	0.234 (0.569)	0.002*** (0.000)	-1.808*** (0.664)	-0.023 (0.066)
kit camaras	Amazon	40	0.178 (0.178)	0.001*** (0.000)	-0.065 (0.362)	-0.033** (0.013)
kit camaras	Mercado Libre	40	0.000 (0.121)	0.000 (0.000)	-1.472*** (0.334)	0.068*** (0.018)
lamina marmol pvc	Amazon	35	0.427 (0.923)	0.010*** (0.001)	-1.047*** (0.357)	0.144*** (0.024)
lamina marmol pvc	Mercado Libre	35	0.159 (0.649)	0.010*** (0.000)	-0.913** (0.381)	0.235*** (0.031)
laptop	Amazon	30	0.163 (3.949)	0.009*** (0.000)	-5.875*** (0.358)	0.159*** (0.042)
laptop	Mercado Libre	40	0.000 (0.342)	0.000 (0.000)	-0.616*** (0.146)	0.029 (0.019)
levis 513	Amazon	40	0.000 (0.000)	0.000*** (0.000)	-0.019* (0.010)	0.001 (0.001)
levis 513	Mercado Libre	40	0.286 (0.695)	0.009*** (0.001)	-6.414*** (0.637)	1.155*** (0.097)
luces led	Amazon	40	0.246 (0.476)	0.001 (0.001)	-0.734*** (0.238)	0.024 (0.021)
luces led	Mercado Libre	40	0.265 (0.659)	0.000 (0.000)	-0.094 (0.581)	0.025 (0.058)
mens pants	Amazon	35	0.000 (0.124)	0.000*** (0.000)	-0.170*** (0.053)	-0.019*** (0.005)
mens pants	Mercado Libre	35	0.573 (2.164)	0.000*** (0.000)	-2.144*** (0.363)	0.072*** (0.020)
mesa comedor	Amazon	35	0.000 (0.234)	0.000** (0.000)	-1.450 (1.052)	0.582 (0.373)
mesa comedor	Mercado Libre	35	0.246 (0.551)	0.003*** (0.000)	-0.467 (0.918)	0.084** (0.035)
mesa jardin	Amazon	30	0.863 (2.942)	0.010*** (0.001)	-0.710** (0.299)	0.061*** (0.015)
mesa jardin	Mercado Libre	40	0.271 (1.163)	0.002*** (0.000)	-0.164 (1.028)	0.060** (0.029)
minisplit inverter	Amazon	30	0.000 (0.119)	0.001*** (0.000)	-0.785*** (0.199)	-0.113 (0.111)
minisplit inverter	Mercado Libre	30	0.302 (0.346)	0.003*** (0.000)	-1.202*** (0.379)	0.072*** (0.014)
motos hot wheels	Amazon	35	0.201 (0.565)	0.001*** (0.000)	-0.213 (0.333)	0.002 (0.009)
motos hot wheels	Mercado Libre	35	0.064 (0.470)	0.000 (0.000)	-2.360*** (0.404)	0.099*** (0.023)
mouse inalambrico	Amazon	30	0.000 (0.547)	0.000*** (0.000)	-0.597 (0.482)	0.175*** (0.031)
mouse inalambrico	Mercado Libre	30	0.668 (6.929)	0.002*** (0.000)	-1.688*** (0.595)	0.017 (0.016)
mueble bano	Amazon	35	0.705 (18.551)	0.000 (0.000)	-0.843** (0.413)	-0.059*** (0.016)
mueble bano	Mercado Libre	35	0.223 (1.067)	0.000 (0.015)	-25.615*** (5.648)	2.719*** (0.477)
notebook	Amazon	30	0.171 (0.400)	0.011*** (0.000)	-1.022*** (0.255)	0.286*** (0.057)
notebook	Mercado Libre	30	0.246 (0.748)	0.010*** (0.000)	-0.398 (0.408)	-0.089 (0.055)
oppo	Amazon	40	0.171 (1.086)	0.009*** (0.000)	-2.953** (1.501)	-0.324*** (0.077)
oppo	Mercado Libre	40	0.660 (2.919)	0.000 (0.001)	-1.629*** (0.502)	-0.026 (0.021)
paneles decorativos	Amazon	30	0.129 (0.339)	0.010*** (0.000)	-1.077* (0.604)	0.045 (0.116)
paneles decorativos	Mercado Libre	35	0.146 (0.371)	0.001*** (0.000)	-1.188** (0.472)	0.156** (0.075)
pantalla 32 pulgadas	Amazon	40	0.187 (0.269)	0.010*** (0.002)	-4.483*** (1.217)	0.186* (0.097)
pantalla 32 pulgadas	Mercado Libre	40	0.000 (0.151)	0.002*** (0.001)	-1.341** (0.585)	0.166** (0.084)
pants de mujer	Amazon	40	0.000 (1.951)	0.001*** (0.000)	-0.513 (0.332)	-0.063* (0.034)
pants de mujer	Mercado Libre	40	0.000 (0.199)	0.000*** (0.000)	-10.195*** (3.172)	0.574*** (0.178)
poco m7	Amazon	30	0.000 (0.884)	0.000 (0.000)	-2.049* (1.093)	-0.027 (0.027)
poco m7	Mercado Libre	30	0.156 (0.883)	0.009*** (0.000)	-1.912** (0.862)	0.185* (0.096)
proyector	Amazon	40	0.627 (1.739)	0.019*** (0.002)	-1.661*** (0.380)	-0.004 (0.059)
proyector	Mercado Libre	40	0.055 (0.373)	0.010*** (0.001)	-1.268 (1.020)	0.503*** (0.139)
redmi note 12 pro plus	Amazon	40	0.021 (0.082)	0.018*** (0.000)	-0.452 (1.437)	0.101 (0.235)
redmi note 12 pro plus	Mercado Libre	40	0.171 (0.753)	0.009*** (0.000)	-58.134*** (16.580)	4.291*** (1.402)
reloj hombre	Amazon	40	0.139 (2.613)	0.008** (0.004)	-0.854*** (0.249)	-0.325** (0.142)
reloj hombre	Mercado Libre	40	0.688 (1.918)	0.000*** (0.000)	-1.183*** (0.240)	0.074*** (0.018)
ring camara	Amazon	30	0.239 (1.273)	0.001*** (0.000)	-0.298 (0.246)	0.159*** (0.048)
ring camara	Mercado Libre	30	0.162 (0.337)	0.010*** (0.000)	-14.554* (7.972)	1.723** (0.838)
shorts de mujer	Amazon	35	0.000 (3.397)	0.001*** (0.000)	-0.353 (0.270)	-0.046* (0.027)
shorts de mujer	Mercado Libre	35	0.000 (0.728)	0.000 (0.000)	-5.890*** (1.488)	0.331*** (0.091)
smart tv	Amazon	35	0.489 (1.234)	0.010* (0.005)	-0.719** (0.298)	-0.157*** (0.036)
smart tv	Mercado Libre	35	0.041 (0.190)	0.010*** (0.001)	-1.843* (1.081)	0.386*** (0.115)
smart watch	Amazon	40	0.157 (0.513)	0.011*** (0.000)	-0.755*** (0.238)	0.091** (0.038)
smart watch	Mercado Libre	40	0.135 (0.150)	0.011*** (0.000)	-5.106 (3.669)	16.784*** (5.308)
teclado pc	Amazon	35	0.000 (0.397)	0.000 (0.002)	-0.319 (0.461)	-0.126*** (0.025)
teclado pc	Mercado Libre	35	0.000 (0.758)	0.000*** (0.000)	-0.412*** (0.132)	0.001 (0.004)
tenis blancos	Amazon	30	0.154 (1.154)	0.009*** (0.000)	-1.112*** (0.203)	-0.047*** (0.016)
tenis blancos	Mercado Libre	30	0.207 (0.393)	0.004*** (0.000)	-2.017* (1.096)	0.302*** (0.082)
tenis de mujer	Amazon	30	0.000 (0.512)	0.002*** (0.000)	-0.443 (0.288)	-0.055* (0.030)
tenis de mujer	Mercado Libre	30	0.144 (0.795)	0.009*** (0.001)	-22.074*** (4.748)	1.258*** (0.288)

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12: Welfare Analysis: Counterfactual Simulation - Unbiased Ranking

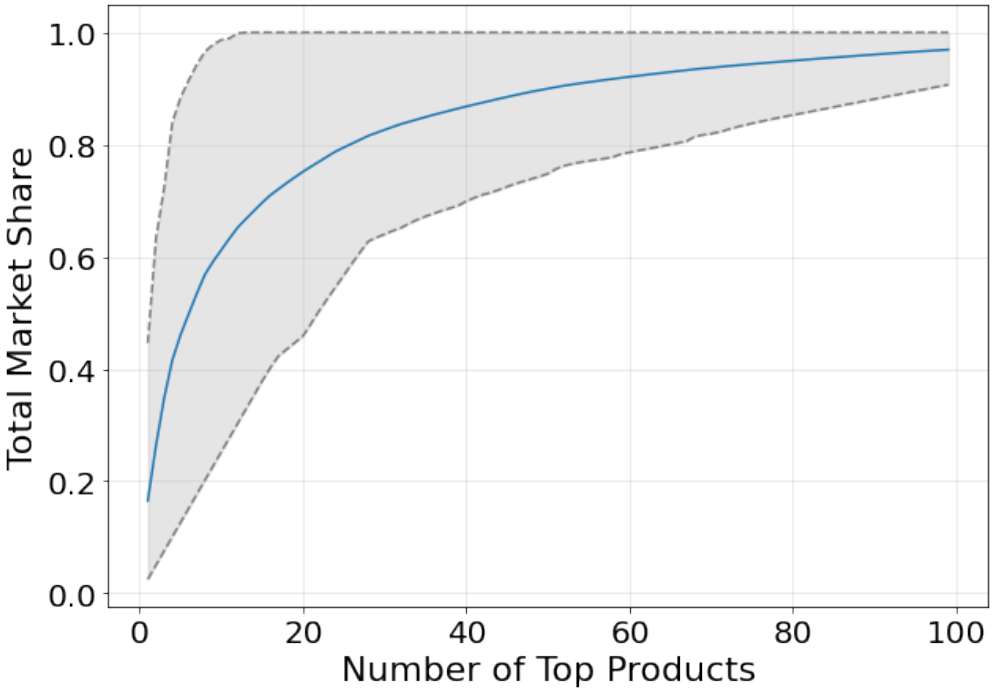
	Baseline	Fixed Prices		Sellers Optimize		Platform Responds	
Outcome	**Level**	**Level**	**% Change**	**Level**	**% Change**	**Level**	**% Change**
Amazon							
Consumer Surplus	\$473.17	\$494.61	4.53%***	\$517.31	9.33%***	\$524.08	10.76%***
		(0.02)		(1.86)		(0.03)	
Producer Surplus	\$519.22	\$537.24	3.47%	\$591.23	13.87%***	\$577.89	11.30%***
		(0.17)		(6.68)		(1.06)	
Platform Surplus	\$302.77	\$310.97	2.71%***	\$330.53	9.17%***	\$347.48	14.77%***
		(0.03)		(1.46)		(2.04)	
ID (%)	53.13	52.04	-2.05%***	50.45	-5.04%***	48.32	-9.05%***
		(5.10)		(4.90)		(6.01)	
Mean Price	\$2,182.27	\$2,166.99	-0.70%***	\$2,012.92	-7.76%***	\$2,007.91	-7.99%***
		(0.01)		(6.42)		(2.30)	
Market Share (%)	34.82	35.24	1.21%***	40.63	16.70%***	41.29	18.60%***
		(0.71)		(0.23)		(1.27)	
Commission (%)	13.07%	13.07%	0.00%	13.07%	0.00%	14.88%	13.89%
		(0.00)		(0.00)		(0.11)	
MercadoLibre							
Consumer Surplus	\$1,137.71	\$1,166.44	2.53%***	\$1,223.74	7.56%***	\$1,219.64	7.20%***
		(1.45)		(5.28)		(0.38)	
Producer Surplus	\$1,048.77	\$1,094.32	4.34%***	\$898.30	-14.35%***	\$842.79	-19.64%***
		(5.08)		(15.50)		(5.31)	
Platform Surplus	\$575.29	\$600.66	4.41%***	\$542.15	-5.76%***	\$539.56	-6.21%***
		(0.09)		(1.21)		(0.17)	
ID (%)	66.08	65.81	-0.40%***	62.26	-5.77%***	62.57	-5.30%***
		(0.10)		(4.51)		(6.71)	
Mean Price	\$2,987.09	\$2,975.71	-0.38%***	\$2,879.85	-3.59%***	\$2,903.45	-2.80%***
		(0.59)		(0.79)		(0.44)	
Market Share (%)	45.18	44.75	-0.93%***	39.36	-12.88%***	38.70	-14.34%***
		(0.09)		(2.19)		(2.32)	
Commission (%)	15.03%	15.03%	0.00%	15.03%	0.00%	17.58%	16.99%***
		(0.00)		(0.00)		(0.12)	
Total Surplus	**\$1,564.98**	**\$1,621.53**	**3.61%*****	**\$1,636.34**	**4.56%*****	**\$1,623.05**	**3.71%*****
		(0.66)		(8.37)		(2.40)	
Bootstrap Samples		100		50		20	

Notes: This table presents the welfare effects of counterfactual scenarios compared to the baseline. Consumer surplus, producer surplus, platform surplus, and total surplus are measured in MXN. Mean price is the average price of products weighted by their market share, so it reflects the products that consumers actually purchase. ID (%) is the market-share-weighted integrated delivery adoption rate. Total surplus is the sum of consumer, producer, and platform surplus across both platforms, weighted by platform market shares. Bootstrap standard errors, computed across bootstrap iterations, are in parentheses. Stars on the percentage changes denote significance of the difference between the counterfactual and baseline means, based on a z-test using the bootstrap standard error of the paired difference: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

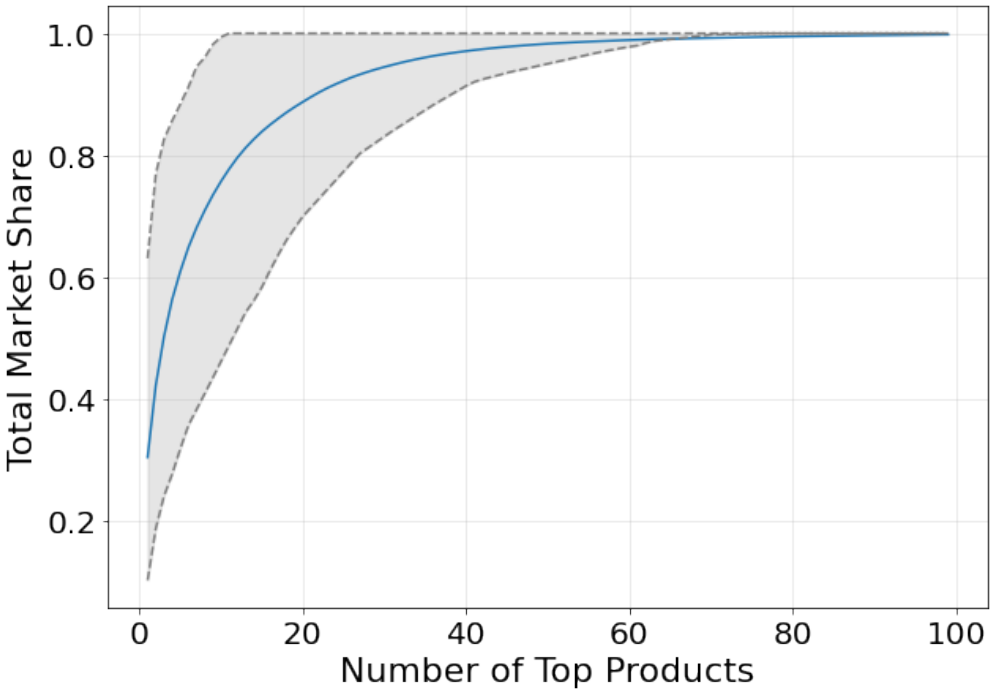
Table 13: Welfare Analysis: Full Divestiture from Mercado Libre

Welfare	**Baseline**	**FBA Only**	**% vs Base**
Amazon			
Consumer Surplus	\$473.17	\$433.42	-8.40%***
		(24.45)	
Producer Surplus	\$519.22	\$506.13	-2.52%***
		(13.31)	
Platform Surplus	\$302.77	\$339.16	12.02%***
		(21.01)	
ID (%)	53.13	64.64	21.68%***
		(3.11)	
Mean Price	\$2,182.27	\$2,343.75	7.40%***
		(35.07)	
Market Share (%)	34.82	32.87	-5.60%*
		(1.08)	
Platform Fee (%)	13.07%	14.76%	12.94%***
		(0.04)	
MercadoLibre			
Consumer Surplus	\$1,137.71	\$1,272.18	11.82%***
		(19.87)	
Producer Surplus	\$1,048.77	\$1,199.37	14.36%***
		(20.09)	
Platform Surplus	\$575.29	\$503.32	-12.51%***
		(13.93)	
ID (%)	66.08	0.00	-100.00%***
		(0.00)	
Mean Price	\$2,987.09	\$2,637.30	-11.71%***
		(87.83)	
Market Share (%)	45.18	49.01	8.48%**
		(1.13)	
Platform Fee (%)	15.03%	17.26%	14.85%***
		(0.08)	
Total Surplus	**\$1,564.98**	**\$1,495.03**	**-4.47%*****
		(50.07)	

Notes: This table presents the welfare effects of the divestiture of Full from Mercado Libre compared to the baseline. Consumer surplus, producer surplus, platform surplus, and total surplus are measured in MXN. Mean price is the average price of products weighted by their market share, so it reflects the products that consumers actually purchase. ID (%) is the market-share-weighted integrated delivery adoption rate. Total surplus is the sum of consumer, producer, and platform surplus across both platforms, weighted by platform market shares. Bootstrap standard errors, computed across bootstrap iterations, are in parentheses. Stars on the percentage changes denote significance of the difference between the counterfactual and baseline means, based on a z-test using the bootstrap standard error of the paired difference: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

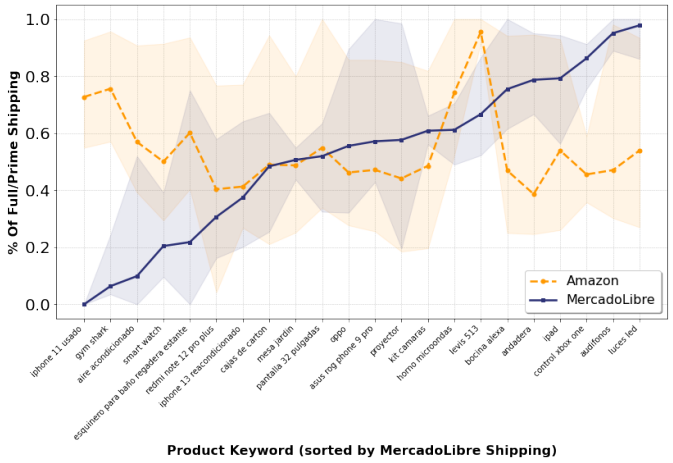


(a) Top Selling: Mercado Libre

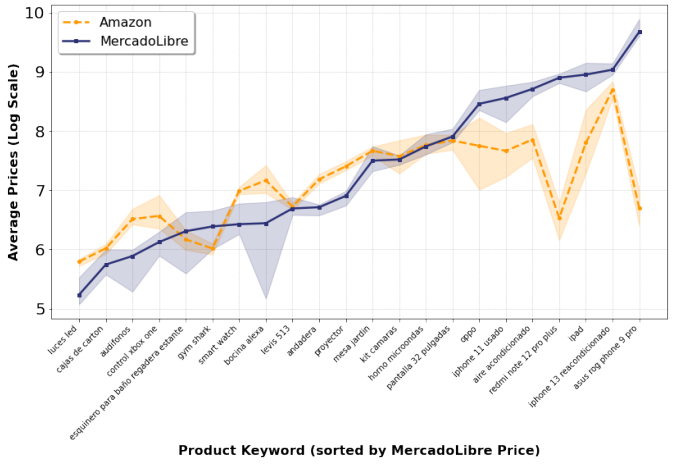


(b) Top Selling: Amazon

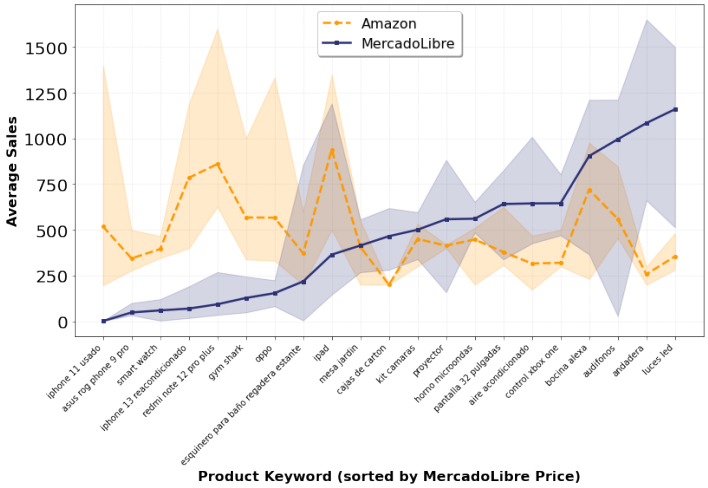
Figure 6: Market Shares of Top Selling Products



(a) Proportion of First-Party Shipping by Market



(b) Average Prices by Market



(c) Average Sales by Market

Figure 7: Statistics by Market on Mercado Libre and Amazon

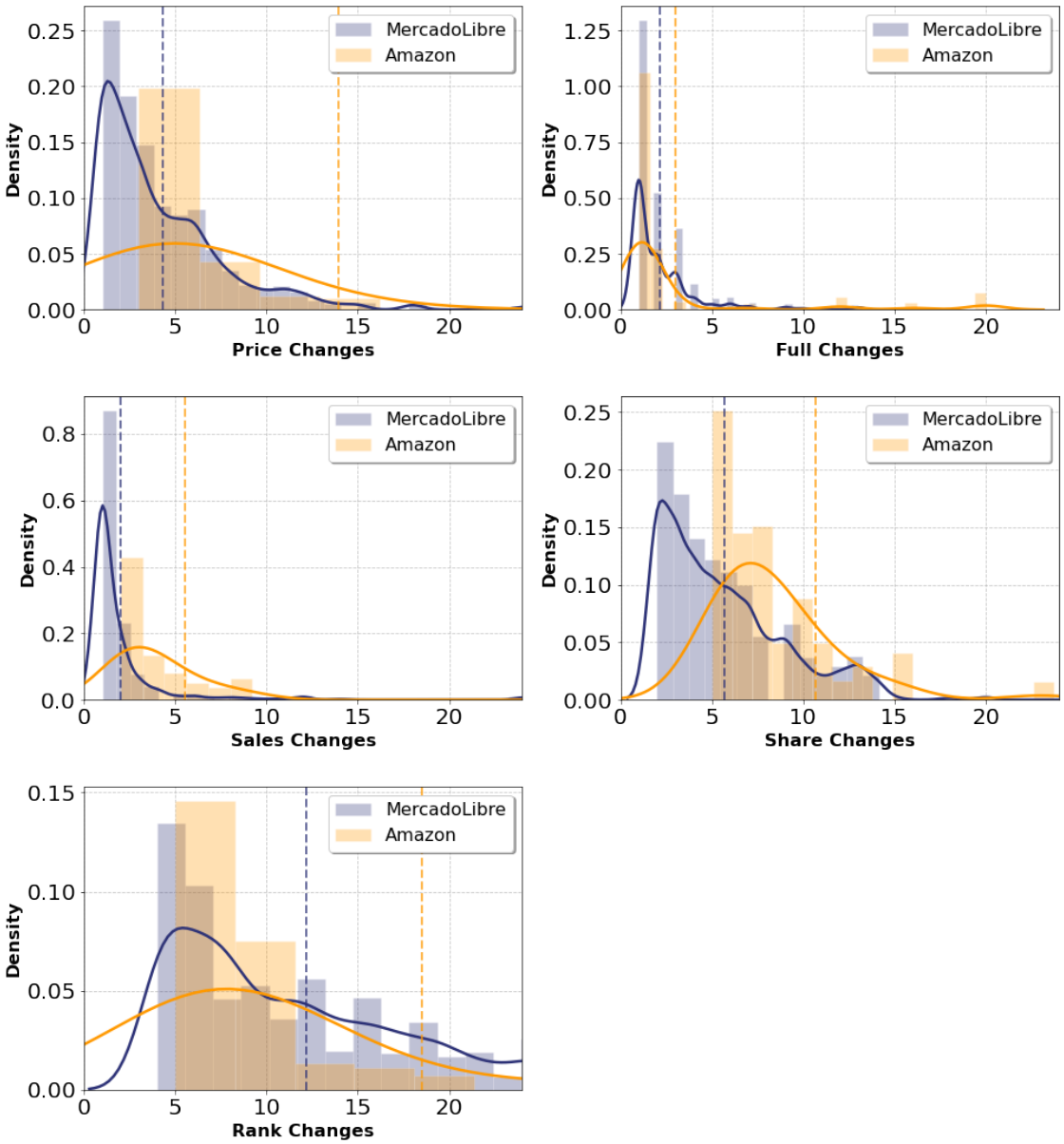
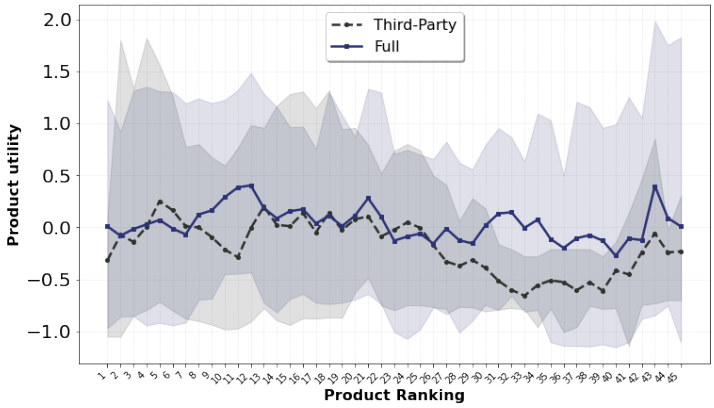
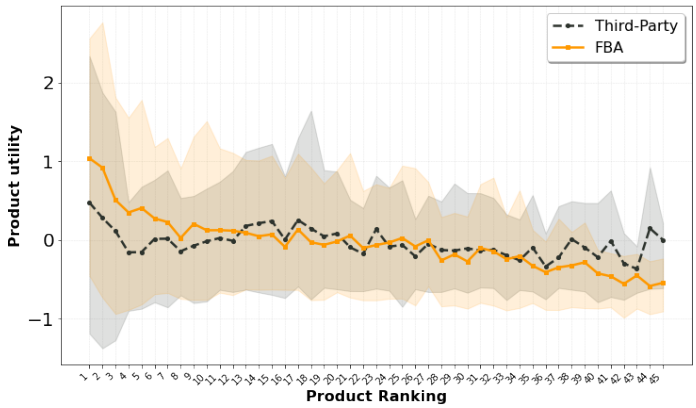


Figure 8: Distribution of Changes in Price, Sales, Ranking and Use of FBA/Full Across Time by Product

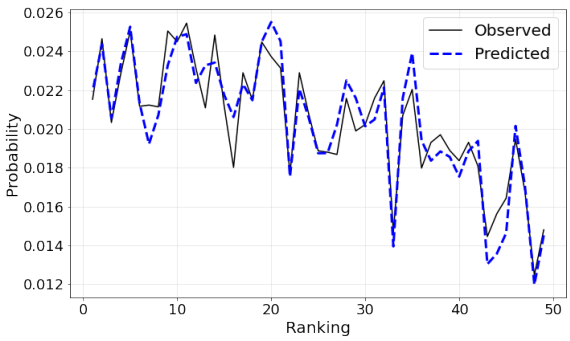


(a) Mercado Libre

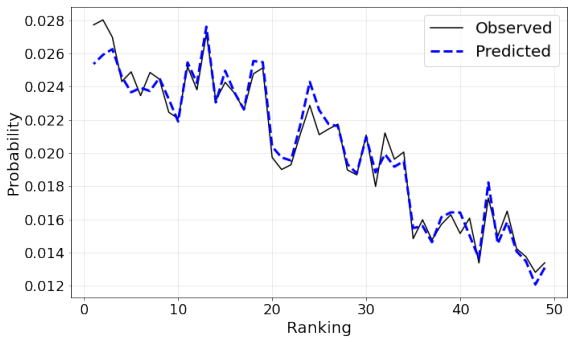


(b) Amazon

Figure 9: Mean product utility by Rank on Mercado Libre and Amazon



(a) Mercado Libre



(b) Amazon

Figure 10: ROL Ranking Probabilities.
Note: The Figure shows the mean observed probability that all products in the sample are placed in a given ranking versus the predicted probability given by the Rank Ordered Logit (ROL) model. A random ranking model would set all probabilities equal for each rank while the ROL matches the trend of the observed probabilities.

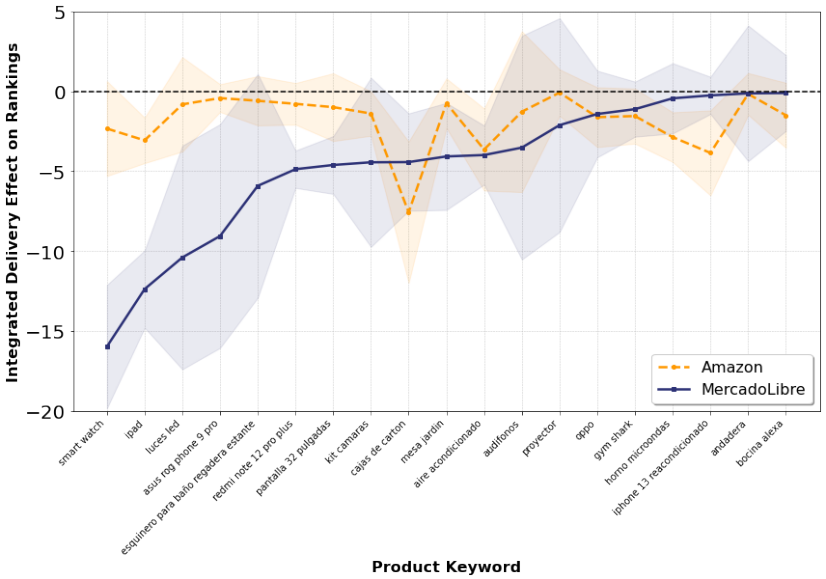


Figure 11: Integrated Delivery Effects on Ranking.
Note: The Figure shows the expected difference in ranking of products using *FBA* or *Full* versus those using third-party delivery across markets using the ROL estimates, all else equal. A negative effect implies that similar products using the integrated delivery systematically appear in lower (better) rankings than those using third party delivery.

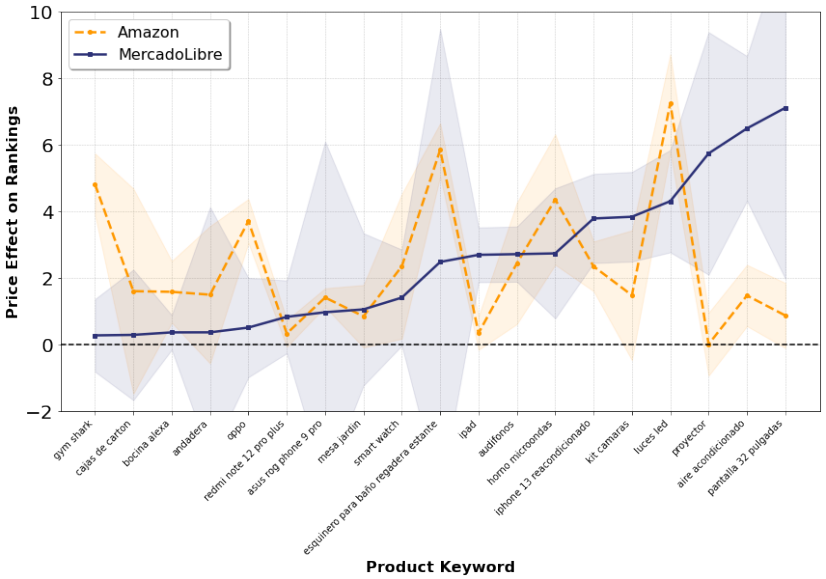


Figure 12: Price Effects on Ranking.
Note: The Figure shows the expected change in ranking when products decrease their prices by 1%, all else equal.