Price Competition Under Information (Dis)Advantage

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Abstract

We examine the impact of asymmetric information access within a vertically integrated e-commerce platform. Using a daily panel, we identify the presence of information advantage for the platform owner: while both the owner and third-party sellers base pricing on past sales, only the owner leverages competitors’ sales. We estimate a price competition model with heterogeneous learning and find that information advantage may be a source of market power, decreasing social welfare compared to symmetric information accesses by either limiting or sharing superior information. Sharing leads to a larger welfare increase by enhancing market efficiencies, benefiting consumers, sellers, and the owner.

Keywords: Price competition; e-commerce; digital platform; data access; information asymmetry; market power

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1 Introduction

Classic theories on information sharing in determining competitive outcomes (e.g., Kühn and Vives, 1995) have gained increased relevance in today’s digital era. Data, often characterized as the “non-rival” new oil (e.g., Varian, 2018), exhibits potential unequal access for firms. We investigate the presence and implications of such disparities within a dominant, vertically integrated platform where the platform owner competes with hosted third parties. Specifically, we identify asymmetric access to historical sales data and quantify its profits and welfare impact in the context of price competition between Amazon and third-party sellers.¹

This empirical context is chosen for two reasons. First, the market structure of vertically integrated platforms offers a unique setting to examine the consequences of asymmetric data access. In our case, the e-commerce platform owner manages all transactions and maintains extensive sales data, while third-party sellers potentially possess less information beyond their own sales. Second, the design of data access within these vertically integrated platforms is important for social welfare (e.g., Crémer et al., 2019).

We compile a daily panel dataset for products on Amazon.com spanning a 7-month period. The dataset comprises over 122,000 products, each with two sellers offering the same product in new condition, allowing us to study price competition in a duopoly market, the most prevalent oligopoly structure on the platform. We collect daily information on price and inventory for each product listing, where each listing represents a seller offering a given product. We use inventory data to approximate daily sales at the listing level.

We begin by presenting simple reduced-form evidence on how sellers set prices based on past sales. The high-frequency pricing and sales data enable us to obtain a plausibly causal understanding of sellers’ learning behaviors. To start, we demonstrate

¹Recent empirical research (e.g., Bajari et al., 2019) highlights the significance of past sales data for demand forecasting in e-commerce.
that sellers tend to gradually decrease their prices when experiencing consecutive days without sales, aligning with learned pessimistic beliefs about the demand state (e.g., Mason and Välimäki, 2011). Subsequently, we find that sellers are likely to increase their prices immediately following a sale event, suggesting that they may adjust their prices in response to beliefs about stronger demand. Both Amazon and third-party sellers alike are highly responsive to their own sales and lack of sales.

Next, we present novel evidence of asymmetric learning contingent on competitors’ sales. Although competitors’ sales data is not publicly available on the platform, platform owner has access to this information and might learn from it. To test this hypothesis, we show that when Amazon’s competitors make sales, Amazon adjusts its prices accordingly. Conversely, third-party sellers do not react to their competitors’ sales. This discrepancy in the ability to respond to competitors’ sales highlights the potential informational advantage Amazon possesses as the platform owner when competing against third-party sellers. To strengthen the point that information, not sophistication, is the driver, we show that although large third-party sellers exhibit stronger responses to their own sales when compared to smaller sellers, their reactions to competitors’ sales remain similarly muted. This interpretation aligns with the findings from our industry surveys.

Moving forward, we build a simple structural model of price competition, allowing firms to hold heterogeneous beliefs about the state of demand. Using the realized sales, we estimate the true demand states $h$. Subsequently, we use a prediction model that utilizes historical true demand states (prior to day $t$) to forecast the current demand state (on day $t$), termed as the best predicted demand state, denoted as $h^{BP}$. The key distinction lies in the fact that true demand states $h$ are determined ex-post, after the realization of day $t$ sales, while best predicted demand states $h^{BP}$ are determined ex-ante, based on past sales data preceding the realization of day $t$.

\footnote{Appendix A considers a toy model of price competition under information advantage and finds that, theoretically, the welfare changes are largely uncertain.}
sales. $h$ and $h^{BP}$ exhibit correlation, with the strength of this correlation, derived from the data, indicating the usefulness of historical sales data in predicting current demand states. Firms’ beliefs regarding the current demand state, depending on their information access, are constructed through a simple reduced-form function of $h^{BP}$. This function is monotonic, with superior data access resulting in beliefs closer to $h^{BP}$. Analogously to the reduced-form analysis, firms’ heterogeneous belief functions are identified by how their prices respond to past sales (or $h^{BP}$).

On the demand side, we assume consumers arrive following a Poisson process, with preferences conforming to a nested logit model. The model groups sellers of a specific product together in one nest and the outside option in another. The utility model incorporates the true demand state as an intercept, allowing for preference heterogeneity through a set of fixed effects and random effects in consumer utility functions. On the supply side, each seller calculates their sales based on their own belief about demand. Using these beliefs, sellers participate in a simultaneous-move pricing game and make pricing decisions.

We estimate the model using the Method of Simulated Moments. Model parameters are selected based on their ability to replicate empirical moments, such as price, sales, and their interactions. Our estimation involves two aspects. First, we employ a full solution approach to estimate the model, which jointly solves the demand and supply model to explicitly account for price endogeneity. We discretize all observed and unobserved states. We utilize numerical integration to compute model moments for unobserved states (i.e., random effects in consumers’ utility function and firms’ cost function). Second, we exploit within-product listing variations in price. To achieve this, we choose a sample of local repricing events for estimation. We assume that within a 3-day time window, price variations are driven by firms’ beliefs or costs, and on average, the underlying demand remains smooth. Our approach requires solving equilibria for 12,960 pricing games for each set of candidate parameters.

We estimate an average own-price elasticity of $-18.96$, in line with existing lit-
erature (e.g., Ellison and Ellison, 2009; Dinerstein et al., 2018). The high own-price
elasticity results from intense competition when two sellers compete head-to-head on
the same product under a shared product page. The average cross-price elasticity
is 18.41, which is high as expected but lower than a classic Bertrand model would
predict. We quantify differences in beliefs between Amazon and third-party sellers.
First, the estimates for own-belief parameters indicate that both Amazon and third-
party sellers possess accurate beliefs about their own demand states. Their levels of
accuracy are comparable, with both aligning well with their respective $h^{BP}$ values,
and Amazon is slightly more accurate. Second, for beliefs about competitors’ de-
mand states, Amazon’s belief aligns with the competitor’s $h^{BP}$. However, third-party
sellers’ beliefs closely resemble random guesses. Overall, these findings are consistent
with the earlier evidence, indicating the presence of heterogeneous learning and an
information advantage for Amazon over third-party sellers.

We conduct several counterfactual analyses to examine the impact of informa-
tion advantage on price competition, specifically: (1) preventing Amazon from using
marketplace data for its own retail business and (2) sharing marketplace data with
third-party sellers. These counterfactuals correspond to proposals that Amazon put
forward in response to EU antitrust investigations.\textsuperscript{3}

In the first counterfactual, we examine a scenario where Amazon is prohibited
from using competitors’ past sales data for pricing. We model this scenario by setting
Amazon’s belief parameter to be identical to that of third-party sellers. Under the
current 15% referral fee, Amazon’s first-party sales and profits decrease by 0.64%
and 0.30%, respectively, while third-party sellers experience a 2.63% increase in sales
and a 2.36% profit gain. While more information increases efficiency, the superior
information also grants market power, allowing the advantaged party discern when
to raise prices. This leads to an anti-competitive effect that outweighs the efficiency

gains.\textsuperscript{4} As a result of removing the information advantage and, consequently, market power, consumer welfare and social welfare improve by 0.48\% and 0.33\%, respectively.

We further examine the role of vertical market structure in our findings by analyzing the scenario where Amazon charges a 0\% referral fee, eliminating its vertical incentives. In this case, when Amazon’s information advantage is eliminated, there is a larger decrease in Amazon’s profits of about 4.68\%, while third-party sellers’ profits increase by 7.26\%. The results suggest that, in the absence of vertical incentives, market power stemming from informational advantage may pose a more prominent concern, reducing social welfare by 0.61\%.

In the second counterfactual, we investigate a situation where Amazon shares its own sales data with third-party sellers, providing equal access to information. We simulate this scenario by adjusting the belief parameter of third-party sellers to match that of Amazon. Our findings indicate a substantial increase of 14.91\% in sales for third-party sellers, while Amazon’s sales experience a 4.08\% decline. Moreover, information sharing leads to a more substantial rise in consumer welfare and social welfare on average, with estimated increases of 2.08\% and 1.65\%, respectively. Sharing information yields a greater social welfare gain than restricting information, despite a lesser average price reduction in the former. The gain mostly comes from the increased information enhancing the matching quality of supply and demand. We further explore the role of vertical incentives as well as information sharing in non-Amazon markets.

In summary, this paper examines price competition between a dominant, vertically integrated e-commerce platform owner and its hosted competitors. We identify the presence of information advantage for the owner. We show that the information advantage may serve as a source of market power, enabling the advantaged party to extract more economic rents. Compared to the current asymmetric information access, eliminating the platform owner’s information advantage decreases its mar-

\textsuperscript{4}See Section 2.2 in Acemoglu (2021) for a related example.
ket power and increases social welfare, while sharing information leads to a more substantial increase in market efficiency.

1.1 Related Literature

This study builds on theories of information sharing in oligopolies (e.g., Vives, 1984; Li, 1985; Gal-Or, 1985). Recent empirical work examines the impact of information disclosure in competitive markets. Rossi and Chintagunta (2016), Luco (2019), and Ater and Rigbi (2023) provide novel evidence on the competitive effects of mandatory price-disclosure policies in offline markets. These studies employ a reduced-form approach, focusing on the transparency of a strategic decision variable important to both firms and consumers. In a concurrent study, Byrne et al. (2023) examine the impact of asymmetric access to competitors’ price information in retail gasoline markets. Our paper introduces past sales information, which can be used as an input for predicting current demand states (e.g., Bajari et al., 2019).

We model firms’ beliefs as a function of past data and identifies these beliefs from the dependence of firms’ strategies on past data. This approach relates to recent empirical studies that examine how firms learn and form beliefs in competitive environments (e.g., Doraszelski et al., 2018; Jeon, 2022; Huang et al., 2022). Moreover,

\(^5\) Classic empirical literature highlights how the disclosure of product quality information affects equilibrium outcomes (e.g., Jin and Leslie, 2003; Tadelis and Zettelmeyer, 2015).

\(^6\) Refer to Fudenberg and Villas-Boas (2006) for the theoretical literature on pricing with consumer-level past sales data.

\(^7\) For a comprehensive review, see Aguirregabiria and Jeon (2020) and Aguirregabiria (2021). Asker et al. (2020) examine competitive information sharing in a dynamic auction environment. Our paper is broadly related to recent work investigating the competitive effects of pricing technologies that adjust according to a rival’s historical prices (e.g., Calvano et al., 2020; Klein, 2021; Clark et al., 2023; Rhodes et al., 2023). Brown and MacKay (2023) present empirical evidence and a model in which firms can differ in pricing frequency and choose pricing algorithms that are a function of rivals’ prices. Asker et al. (2023) study the prices generated by AIs using different learning protocols when there is market interaction.
the heterogeneities in beliefs identified among Amazon and third-party sellers are related to the work of Goldfarb and Xiao (2011) and Hortacsu et al. (2019), who employ the Cognitive Hierarchy model to empirically investigate variations in the strategic sophistication of firms.

This study focuses on the design of access to data for sellers within the context of a vertically integrated platform, relating to the incentives and efficiency in vertically integrated markets (e.g., Hart et al., 1990; Rey and Tirole, 2007). Specifically, we contribute to a new and growing empirical literature on vertically integrated platforms that focuses on the design of information for consumers and its implications (e.g., Chen and Tsai, 2019; Lee and Musolff, 2021; Lam, 2021; Raval, 2022; Farronato et al., 2023; Reimers and Waldfogel, 2023). To the best of our understanding, we present a perspective that has yet to be empirically explored: the platform owner’s information advantage over third-party players.\footnote{The closest empirical work to this perspective is Zhu and Liu (2018), which examines platform owners entering third-party selling markets but does not specifically identify the owner’s information advantage (see also Crawford et al., 2022). High-frequency variations in price decisions and sales information provide an opportunity to identify information advantage in this empirical context. Hagiu et al. (2022) and Gutierrez (2021) examine the implications of vertically integrated platforms from a broader perspective. In a broader context, our study addresses small firms’ access to non-personal and non-rival data (e.g., Jones and Tonetti, 2020; Acemoglu, 2021; Bergemann et al., 2022).}

In a theoretical work, Madsen and Vellodi (2022) investigate how a platform owner may leverage its informational advantage to imitate products offered by third-party sellers.

The remainder of this paper is organized as follows. Section 2 provides an overview of the empirical context. Section 3 describes the data and provides summary statistics. Section 4 presents evidence of asymmetric seller learning. Section 5 outlines the structural model. Section 6 discusses our estimation method and identification strategy. Section 7 presents our estimates and results from the counterfactual analyses. Finally, Section 8 concludes the paper. Additional technical details and robustness checks are available in the appendices.
2 Background

Amazon is a leading online retailer that has over 2.5 million third-party sellers on its platform as of 2021. These sellers are independent businesses that use Amazon’s platform to sell their products to customers worldwide and make up a significant portion of Amazon’s overall sales. In addition to third-party sellers, Amazon also sells its own products, including both private-label and branded products, directly competing with these third-party sellers.\(^9\)

Amazon’s Information Advantage There has been much discussion in academic and policy circles about Amazon’s dual role as both the owner of its marketplace and as a retailer that competes with other sellers on the platform. This has raised concerns about Amazon potentially utilizing data from third-party sellers, to which it has access as the platform owner, in ways that may not align with the best interests of its third-party sellers or consumers. Some have raised concerns that Amazon may misuse this data in its pricing and product launching decisions, or exert its influence in other unfair ways.

While we focus on Amazon’s US store, in July 2019, the European Commission initiated an inquiry into Amazon’s utilization of marketplace vendor data.\(^10\) By November 2020, the Commission issued a Statement of Objections, highlighting that “very large quantities of non-public seller data are available to employees of Amazon’s retail business and flow directly into the automated systems of that business, which aggregate these data and use them to calibrate Amazon’s retail offers and strategic business decisions to the detriment of the other marketplace sellers. For example,

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9\(^\)Third-party sellers can operate under either the “Fulfillment by Amazon” (FBA) or “Fulfillment by Merchant” (FBM) program. Under the FBA program, sellers can send their products to an Amazon fulfillment center, where Amazon handles shipping and related services. However, in addition to referral fees, FBA sellers also incur extra FBA fulfillment fees. Refer to https://sell.amazon.com/pricing#fulfillment-fees for further details.

10\(^\)See https://competition-cases.ec.europa.eu/cases/AT.40462.
it allows Amazon to focus its offers in the best-selling products across product cat-
egories and to adjust its offers in view of non-public data of competing sellers.” ¹¹

In December 2022, Amazon pledged to refrain from using marketplace seller data, specifically including “sales data,” for its retail operations, which specifically covers “Retail Operations decisions to set the prices of ASINs (i.e., products).” ¹², ¹³

**Sales Information on Amazon**  Data plays an increasingly critical role in shaping strategic decisions, and its impact on a company’s performance can be significant (e.g., Bajari et al., 2019). One way of demonstrating this importance is by using sales data to forecast demand and inform pricing decisions. Amazon and its third-party sellers are known for dynamic pricing (also known as algorithmic pricing). The prices of products on the site may vary in response to changes in customer demand and competitors’ actions based on the information sellers have learned.

Our focus is on past sales information. Theoretically, the cost of providing sales data is similar to that of providing price data. While price data is transparent and relatively inexpensive to obtain through public APIs, sales data is not. To put this into perspective, we conduct a survey covering 19 prominent e-commerce platforms across the US, China, Europe, Japan, and Southeast Asia. We find that 47.4% of these platforms disclose sales data. Among them are platforms such as eBay, Taobao, Allegro, AliExpress, and Shopee (refer to Appendix B for details).

As the platform owner, Amazon oversees all transactions and maintains extensive sales data, allowing it to access this information with virtually no marginal cost. Conversely, third-party sellers can observe their own sales but potentially have less

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¹³The actual implementation is expected to occur later than initially pledged. Furthermore, since our study focuses on the US marketplace, the adjustments made by the European marketplace are not expected to directly affect the sellers included in our sample, as evidenced by the absence of noticeable changes in the data.
information beyond their own sales figures.\textsuperscript{14} 

Inferring individual listing sales within a product category is challenging based on the publicly available information in the marketplace. However, there are a few approaches that can provide some insights into competitors’ sales. Amazon’s primary sales metric, the product’s sales rank, consolidates sales data from all listings of a given product and ranks its total sales within its product category. Though third-party sellers can utilize their own sales data and sales rank to estimate competitors’ sales to a certain extent, the information is limited, as the sales rank only represents a ranking and not the actual number of sales. Consequently, it can be influenced by sales of other products.

Services like Jungle Scout offer professional sales estimation for sellers, but the cost is substantial. As of April 15th, 2023, tracking 20 products costs $349 per year.\textsuperscript{15} Another method involves manually monitoring competitors’ inventory and using high-frequency inventory changes to infer sales (e.g., He et al., 2022). However, this approach is also labor-intensive and sometimes impractical.

\textsuperscript{14}There were practices of potential A/B testing conducted by Amazon, indicating the possible disclosure of some form of “sales data.” Industry researcher Waters (2023) notes that “the introduction of public-facing sales data on Amazon is part of a broader trend. After years of holding tight to its customer information, Amazon is making more and more of its data available to brands... Ideally, we want brands to use sales data to gain a richer view of how they compare to their competitors.” See Appendix B for details. The public disclosure of sales data is still in its early stages, and there is no indication of disclosing seller-listing level sales data, which is our focus.

\textsuperscript{15}See https://www.junglescout.com/pricing/.
3 Data

We collect a daily panel dataset from Amazon.com for a period of 7 months, covering from October 2022 to May 2023, for the Home & Kitchen category.\textsuperscript{16} We follow a daily routine for collecting data on the final set of approximately 122,000 products. We use the historical information from Keepa.com to identify products that had an average of between 1.5 to 2.49 listings in new condition over the past 90 days. From this pool of candidate products, we select the most popular products based on their average sales rank over the past 30 days, excluding those with the identical sellers offering products in different conditions or fulfillment methods. We also collect data for a small sample of 2,400 products in two-hour interval to complement the main daily dataset for some robustness checks.

We gather information on different aspects of each seller of a given product, such as its price, shipping fee, seller types, and inventory. We use the current available quantity of a product for purchase on the website as our measure of inventory. When the available inventory matches the maximum quantity that can be purchased in a single transaction (e.g., 999 or a purchasing limit), we consider the inventory as unknown and do not use it for our analysis. These missing data are less common for products in the Home & Kitchen category than in other categories, such as Electronics.

3.1 Summary Statistics

In Table 1, we present statistics for the key variables in our data, separated into seller types whether they are third-party sellers or Amazon itself. Among the product listings in our dataset, 23\% come from Amazon.

\textsuperscript{16}The Home & Kitchen category on Amazon is one of the largest, comprising a wide range of products commonly purchased by consumers, including kitchen appliances, cookware, and home décor. It is also the most popular category among sellers, according to a report by Jungle Scout (see https://www.junglescout.com/amazon-seller-report/?utm_source=twitter&utm_medium=organic&utm_content=report&utm_campaign=sots_2022).
The Price variable is the amount consumers pay for a single unit of the listed product, excluding shipping fees. In our data, third-party sellers have an average price of $49.25, while Amazon has an average price of $66.89. Differences in price levels can be driven by both product and seller-level preferences and costs, which we will separate in our structural estimation. See Appendix C for the discussion of price variation. The Shipping variable is a fixed fee charged per order by the seller.\textsuperscript{17} Shipping fees change infrequently (less than 0.3%) in the data and are absorbed by fixed effects in our analysis.

The Inventory variable indicates the maximum number of units of a product that is available for purchase. Typically, Amazon has a larger inventory than third-party sellers, with average inventory levels of approximately 92.40 compared to 79.93, respectively. We define sales based on daily changes in inventory. For instance, if the inventory decreases from 10 on day \( t - 1 \) to 9 on day \( t \), we assign a sale of 1 for day \( t \).\textsuperscript{18} On average, daily sales for a product in our dataset amount to approximately 0.14 – 0.15. Appendix D discusses concerns related to potential bias in sales estimates due to restocking within a given day. We use the smaller dataset collected at two-hour intervals and show that the probability of underestimating sales is less than 1% when the inventory data frequency is daily.

The Fulfilled By Amazon variable indicates whether a seller uses Amazon’s Fulfilled by Amazon services. All products sold by Amazon are fulfilled by Amazon, while 14% of product listings sold by third-party sellers in our dataset are fulfilled by Amazon. The number of seller ratings is commonly used by industry practitioners to

\textsuperscript{17}On average, third-party sellers charge a shipping fee of approximately $2.71, while Amazon charges an average shipping fee of $0.02. In most cases, shipping is free for both Amazon and third-party sellers who use Fulfillment by Amazon services. However, special handling products such as oversized or frozen items may have exceptions.

\textsuperscript{18}We exclude cases where the inventory decreases by more than 100, as significant inventory reductions is likely due to sellers manually adjusting their inventories instead of sales. We also exclude cases where stock increases as it is likely due to restock. The assumption is that sales and restock events are unlikely to happen in the same period if the length of the period is small enough.
infer seller size.\textsuperscript{19} We use it to define large and small third-party sellers in Section 4.4. The third-party sellers in the data have a median of 595 ratings.\textsuperscript{20}

Table 1: Summary Statistics of Product Listings by Third-Party Sellers and Amazon

<table>
<thead>
<tr>
<th></th>
<th>Third-Party Sellers</th>
<th></th>
<th>Amazon</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>STD</td>
<td>Mean</td>
</tr>
<tr>
<td>Price ($,$)</td>
<td>49.25</td>
<td>26.58</td>
<td>54.52</td>
<td>66.89</td>
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<tr>
<td>Shipping Fee ($,$)</td>
<td>2.71</td>
<td>0.00</td>
<td>7.44</td>
<td>0.02</td>
</tr>
<tr>
<td>Inventory</td>
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<td>20.00</td>
<td>155.38</td>
<td>92.40</td>
</tr>
<tr>
<td>Sales</td>
<td>0.15</td>
<td>0.00</td>
<td>1.89</td>
<td>0.14</td>
</tr>
<tr>
<td>Fulfilled By Amazon</td>
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<tr>
<td>Number of Seller Ratings</td>
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<td>Number of Observations</td>
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</tr>
</tbody>
</table>

Note: The summary statistics in Table 1 include the price, shipping fee, fulfillment by Amazon status, inventory, and sales for all listings from third-party sellers and Amazon, respectively.

4 Reduced-Form Analysis

In this section, we use the high-frequency dataset to investigate sellers’ pricing behaviors. We present reduced-form evidence to support the idea that sellers adjust their prices based on past sales: (1) prices tend to decrease when there are no recent sales, (2) prices immediately increase in response to sales, and (3) Amazon and third-party sellers differ in their ability to use competitor sales information to adjust their pricing, with Amazon being more responsive to competitor sales.

\textsuperscript{19}See \url{https://www.marketplacepulse.com/top-amazon-usa-sellers}.

\textsuperscript{20}On Amazon, consumers can rate sellers that they have purchased from. This seller rating contains feedback for all products listed by a specific seller. Amazon cannot be rated by consumers, so there are no seller-level ratings available for Amazon.
We define the following notation. Let \( m \in M \) be a product market. Let \( j \in J = \{1, 2\} \) indicate a seller. Let \( t \in T \) denote calendar time. We denote the sales and price in product market \( m \) by seller \( j \) on calendar time \( t \) as \( q_{m,j,t} \in Q \subseteq \mathbb{N} \) and \( p_{m,j,t} \in P \subseteq \mathbb{R}^+ \), respectively. Our data consists of a panel of product listings with subscripts \((m, j, t) \in D \subseteq M \times J \times T\). We define a sample selection procedure that takes a subset of data with a subscript \( D_c \subseteq D \) satisfying condition \( c \in C \) and re-index the data in an ordered manner. We denote this re-indexing procedure as \( S : D_c \rightarrow S \subseteq \mathbb{N} \). We use this sample selection procedure with varying selection conditions \( c \) in the reduced-form analysis.

4.1 Sellers decrease their prices when they do not make any sales

When there is no sales, sellers may become pessimistic about demand, and decrease their prices (e.g., Mason and Välimäki, 2011; Huang et al., 2019). In order to test this hypothesis, we select cases where sellers experience no sales on consecutive days and observe how they adjust their prices over this period. We define such events as the set of “no-sales” events:

\[
S^{\text{no sales}}_\tau = \{S(m, j, t) \in N \mid q_{m,j,t+r} = 0, \forall r = 0, \ldots, \tau - 1\}.
\]

To analyze these events, we let \( \tau = 7 \) and estimate the following regression specification:

\[
y_{s,\tilde{t}} = \sum_{\tau=2}^{7} \gamma_{\tau} \times 1(\tilde{t} = \tau) + \psi_s + \epsilon_{s,\tilde{t}}, \quad \forall s \in S^{\text{no sales}}_\tau \land \tilde{t} = 1, 2, \ldots, 7, \quad (1)
\]

where \( \tilde{t} \) denotes the event study time, which ranges from 1 to 7. The outcome of interest for a given event \( s \) on day \( \tilde{t} \) is denoted by \( y_{s,\tilde{t}} \). The indicator variable \( 1(\tilde{t} = \tau) \) takes the value of 1 if the observation corresponds to event day \( \tau \). To allow

\footnote{Our results remain consistent regardless of the selection of \( \tau \). The choice of \( \tau = 7 \) enhances trend visibility compared to smaller values of \( \tau \) and mitigates potential selection concerns associated with larger \( \tau \) values.}
for comparisons of the effects on other days, we normalize the coefficient of the day \( \tilde{t} = 1 \) dummy to zero. The fixed effects for each event are represented by \( \psi_s \).\(^{22}\)

We investigate how price levels change by examining \( p_{s,\tilde{t}} \) as the outcome variable, which provides insights into the overall pricing behavior surrounding the event. In Figure 1, we present the estimates of \( \gamma_\tau \) from Equation 1 with \( p_{s,\tilde{t}} \) as the dependent variable for third-party sellers and Amazon, respectively, with the price level of the first day normalized to zero. The average price level decreases during consecutive days of no sales. Specifically, after seven days of no sales, third-party sellers’ prices decrease by about $0.1, and Amazon’s prices decrease by approximately $0.3.\(^{23}\)

Figure 1: Price Levels during Consecutive Days of No Sales

Note: Figure 1 shows the estimates from Equation 1 during consecutive days of no sales using the price level as the dependent variables for third-party sellers and Amazon, respectively. The robust standard errors are clustered at the product level.

\(^{22}\)\( \psi_s \) represents a more granular level than product fixed effects, and enables us to compare prices within a given product and within neighboring days.

\(^{23}\)There is heterogeneity in level changes between Amazon and third-party sellers. Plausibly, Amazon and third-party sellers face different demand parameters and exercise varying degrees of market power, resulting in different responses. The structural model introduced later can address the limitations of the reduced-form evidence and incorporate the heterogeneity in demand primitives.
4.2 Sellers increase their prices based on their sales

We demonstrate that sellers raise their prices in response to high demand state, which is indicated by their sales. To isolate the effect of sales on prices, we filter the data to include only cases where sellers did not make any sales in the past few days leading up to the event (e.g., day -3 to day -1) and made sales on the event day (day 0). Formally, we define the set of “sales” event as follows:

$$S_{\text{sales}} = \{S(m,j,t) \in \mathbb{N} | q_{m,j,t} > 0 \land q_{m,j,t-r} = 0, \forall r = 1, \ldots, \tau\}.$$ 

Our previous analysis (shown in Section 4.1) demonstrates that sellers typically decrease their prices when they do not make any sales, which would naturally result in a downward trend when the data is restricted to periods where sellers have no sales. To control for this effect, we allow for a linear trend in our event study design. We run the following regression and set $\tau = 3$:

$$y_{s,\tilde{t}} = \sum_{\tau=-3,\tau\neq-1}^{3} \gamma_{\tau} \times 1(\tilde{t} = \tau) + \eta \times \tilde{t} + \psi_{s} + \epsilon_{s,\tilde{t}}, \forall s \in S_{\text{sales}}^{3} \land \tilde{t} \in \{-4, \ldots, 3\}. \quad (2)$$

In Equation 2, $\tilde{t}$ represents the number of days relative to a sales event day, ranging from -4 to 3, and $y_{s,\tilde{t}}$ represents the outcome variable for event $s$ on day $\tilde{t}$. The indicator variable $1(\tilde{t} = \tau)$ takes a value of 1 if the observation is on event day $\tau$. The coefficient of the day -1 dummy is normalized to zero.\footnote{We include data from $\tilde{t} = -4$ in this regression. This is necessary for the rank condition, as allowing for a linear trend parameter $\eta$ results in 8 parameters conditional on each event, and we need at least 8 data points for each event.}

We proceed by examining how price levels change by using $p_{s,\tilde{t}}$ as the outcome variable. Figure 2 shows that the average price for both Amazon and third-party sellers increases following a sales event. Moreover, the price level increase is notably higher for Amazon compared to third-party sellers, with an average increase of around $0.4 for Amazon and $0.1 for third-party sellers.
4.3 Heterogeneity in Learning from Competitor’s Sales

Sellers can learn not only from their own sales, but also from their competitors’ sales provided that information is available. In such cases, sellers may increase their prices when their own demand is also high relative to the outside option or decrease them when their listings are less competitive than that of their competitors. As discussed in Section 2, competitors’ sales is not directly visible for third-party sellers on the website. Amazon, as a dual-role platform, might have direct access to this information and can use it when setting prices. Consequently, we expect that Amazon is more responsive to competitors’ sales compared to third-party sellers.

We define a set of “competitor’s sales” events for a seller $j$ in a duopoly market, where $-j$ represents the seller’s competitor:

$$
\mathcal{S}_{r}^{c-sales} = \{S(m, j, t) \in \mathbb{N} \mid q_{m, -j, t} > 0 \land q_{m, -j, t-r} = 0, \; \forall r = 1, \ldots, r \}.
$$
Next, we examine Equation 2 using observations from competitor sales events, where \( s \in S_{\text{c-sales}} \) and \( \tilde{t} \in \{-4, \ldots, 3\} \). For transparency, we do not control for a competitor’s price in this analysis since the competitor’s price could be seen as a collider variable. Our emphasis is on the focal seller’s price alone, not in relation to a competitor’s price. We address price simultaneity more directly in Section 5.

In Figure 3, we present the estimates of \( \gamma_{\tau} \) using the price as the dependent variable. We find that, on average, Amazon tends to lower its price level in response to competitors’ sales.\(^{25}\) The price reduction aligns with the theory that Amazon learns that the competitor’s offer is more appealing to consumers and decides to lower its own price.\(^{26}\) On the other hand, the price levels of third-party sellers remain insignificantly different from zero following a competitor’s sale.

### 4.4 Discussion: Interpreting the Results

We discuss the interpretation of our results and robustness checks that highlight the information mechanism.

**Information Disadvantage vs. Sophistication** The reduced-form results align with our survey on Amazon’s in-house repricer and leading industry repricers, as discussed in Appendix E. While most repricers are contingent on competitors’ prices and own sales, none of them is contingent on competitors’ sales, potentially due to the lack of information.

However, this leads to the question of whether exceptionally large sellers might develop their proprietary systems to price based on competitors’ sales. We examine this further in Appendix F. Specifically, we separately examine the response patterns

\(^{25}\)This result does not imply Amazon’s *equilibrium average* price is lower under information advantage.

\(^{26}\)This pattern contrasts with dynamic price competition when there are both perishability and capacity constraints (e.g., Chen and Jezierski, 2022; Betancourt et al., 2022). In the absence of demand learning, competitors’ sales result in supply scarcity and incentivize price increases.
Figure 3: Price Levels After a Competitor’s Sales Event

![Graphs showing price levels for Amazon and Third-Party Sellers before and after a competitor’s sales event.](image)

(a) Amazon

(b) Third-Party Sellers

Note: Figure 3 displays the estimates from Equation 2 using the price level as the dependent variable for third-party sellers and Amazon, respectively, before and after a competitor’s sales event. The vertical line indicates the day of a competitor’s sales event. The pre-trend is controlled by the linear trend $\eta$. The robust standard errors are clustered at the product level.

It is plausible that large sellers might be more sophisticated or better equipped with technology. If our reduced-form evidence is driven by seller sophistication or technology rather than information, we would expect to observe that large sellers respond more similarly to Amazon and differ from small sellers. While large third-party sellers exhibit larger responses in price levels compared to small third-party sellers in response to their own sales events, both large and small third-party sellers are unresponsive to the competitor’s sales event. This further suggests that the heterogeneity in responses to competitor’s sales events is driven by information rather than the level of sophistication or technology.

**Learning Competitor’s Sales from Competitor’s Prices** Another theoretical consideration is whether third-party sellers can learn from Amazon’s price changes
to infer if Amazon is experiencing sales. However, in practice, this appears unlikely based on empirical data. Among all the price variations presented in Appendix C, only 13.17% and 12.67% of the price adjustments represent instances where Amazon and third-party sellers, respectively, adjust prices within 3 days following a sales event. Many other factors, such as demand and cost shocks, can trigger price changes. As further supported by our event study results, the empirical relevance of this theoretical consideration is limited within our dataset.

Evidence on Price Adjustment and Autocorrelated Demand In Appendix G, we examine the frequency of price increases and decreases and find consistent evidence with the price level responses. Additionally, in Appendix G.3, we present additional evidence that prices are affected by past sales, and demand exhibits autocorrelation.

Tacit Collusion Tacit collusion based on sales information is not a main concern to our study, as competitors can easily react to competitors’ prices instantly (see Appendix E). Sales are stochastic and difficult to control precisely, and they are unlikely to be a primary coordination tool among competitors, especially given the transparency of prices. Furthermore, we examine our bi-hourly data, as used in Appendix D, and similar to the daily dataset, we did not find any pre-existing trend in prices before sales events. This suggests that the sales event is not confounded by pre-existing price events. Lastly, the comparison provided in Appendix F between large and small third-party sellers does not support the notion that asymmetric price patterns are driven by the asymmetric incentives between dominant and small sellers.

5 Model

To motivate the study, we first solve a simple theoretical model of linear demand in a duopoly price competition. We find that the welfare results are mostly theoretically ambiguous. This ambiguity is primarily driven by the tension between intensified
competition in some demand states and softened competition in others, and it depends on the value of several parameters in the model. Further discussion is provided in Appendix A.

To better understand the impact of information advantage and resolve the theoretical ambiguity, we develop and estimate an empirical structural model. The structural estimation complements our reduced-form analysis in several aspects. First, it allows for an explicit treatment of price simultaneity. Second, it measures heterogeneous primitives of demand and supply and provides a quantitative assessment of the heterogeneous information and beliefs. Third, it facilitates the quantification of profits and welfare under counterfactual designs for data access.

5.1 Timing

We define a market $m$ which consists of a single product with two sellers engaging in duopoly price competition in period $t$, with listings from seller $j \in J_{m,t} \subseteq \{1, 2\}$. Consumers have nested logit preference and decide which of the two sellers to buy from or choose not buying (i.e., the outside option). Seller $j$ can have one of two types defined as $a(j) \rightarrow A = \{0, 1\}$ where 0 and 1 indicate third-party sellers and Amazon respectively. We use the notation $-j$ to denote seller $j$’s competing seller in the same market $m$. The timing of the game is the following:

1. At the onset of time $t$, the sequence of past demand states is realized and represented as $H_{m,j,t} = \{h_{m,j,\tau}, h_{m,-j,\tau} : \tau \leq t - 1\}$. Using the information as input, the algorithm generates the best predicted demand states $h_{m,j,t}^{BP}$ and $h_{m,-j,t}^{BP}$.

2. Sellers form beliefs about their own demand states and competitor’s demand states according to $h_{m,j,t}^{BP}$ and $h_{m,-j,t}^{BP}$. Sellers observe random draws for utilities and marginal costs of both products, which include additional information that deviates from $h_{m,j,t}^{BP}$ and $h_{m,-j,t}^{BP}$. 

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3. Based on their individual beliefs about current demand states, seller \( j \) and its competitor \(-j\) engage in a simultaneous move pricing game.

4. Upon arrival, consumers make purchasing decisions according to prices and actual demand states.

5. Sales are determined, and the market proceeds to step 1 for the subsequent period \( t + 1 \).

### 5.2 Consumer Demand

We outline the demand model below. Let \( I_{m,t} \) be the number of consumers with unit demand arriving at period \( t \) in market \( m \). The arriving demand \( I_{m,t} \) follows a Poisson distribution according to

\[
I_{m,t} \sim \text{Poisson}(\lambda_{m,t}).
\]

We set \( \lambda_{m,t} \) to a large value (i.e., 20), and our estimates are robust with various different values. For market \( m \) in period \( t \), the utility of an arriving consumer \( i \) choosing alternative \( j \in J_{m,t} \cup \{0\} \) is given by

\[
u_{i,m,j,t} = x'_{m,j,t} \beta - \alpha \times p_{m,j,t} + \xi_{m,j,t} + v_{i,m,g(j),t}(\rho) + \rho \times \epsilon_{i,m,j,t},
\]

where \( x'_{m,j,t} \) is a vector of seller characteristics, such as whether the seller is Amazon and whether the seller uses fulfillment by Amazon services, \( p_{m,j,t} \) is the price of seller \( j \) in market \( m \) at time \( t \), \( \xi_{m,j,t} \) is a seller-specific demand shock that changes over time and is important for modeling seller learning (to be discussed in Section 5.2.1), and \( v_{i,m,g(j),t} \) is a nested logit random taste that is constant across sellers and differentiates the “inside” good when \( g(j) = 1 \) from the “outside” option of no purchase when \( g(j) = 0 \). The variable \( \rho \in (0,1] \) is the intraclass correlation coefficient, which measures the correlation of the unobserved factors influencing the utility of different options within the same nest. \( \epsilon_{i,m,j,t} \) is an independently and identically distributed error term (across products and consumers) that follows the logit distribution.
The error structure \( v_{i,m,j} + \rho \times \epsilon_{i,m,j} \) is assumed to follow the distributional assumption necessary to generate the classic nested logit purchase probability, where the two nests consist of all the inside options and the outside option. When \( \rho = 1 \), consumers follow a simple logit decision rule on all alternatives, including the outside option. For simplicity, we define

\[
\delta_{m,j,t} = x_{m,j,t}' \beta - \alpha \times p_{m,j,t} + \xi_{m,j,t}.
\]

The mean utility of the outside option is normalized to zero \( \delta_{m,0,t} = 0 \). This means that the utility of the outside option, where \( j = 0 \), follows the error term \( \epsilon_{i,m,0,t} \).

### 5.2.1 Demand State

One important component of the demand function is the alternative-specific intercept \( \xi_{m,j,t} \), which represents the unobserved factors that affect the utility of a particular seller. This variable varies over time and is partially unknown to sellers before its realization:

\[
\xi_{m,j,t} = \varphi \times h_{m,j,t} + \nu_{m,j,t}, \quad \text{where } \nu_{m,j,t} \sim N\left(0, \sigma^2\right). \tag{4}
\]

In the presence of demand uncertainty, the demand state \( h_{m,j,t} \) is not perfectly observed by sellers until after time \( t \), when the actual sales and market outcomes are realized. This means that sellers do not perfectly observe but instead hold a belief about the true demand level (based on historical information). On the other hand, the researcher, at the time of analysis, can infer true demand states based on realized sales.

The second component in \( \nu_{m,j,t} \) denotes the seller-specific error terms with zero mean and a variance of \( \sigma^2 \). The error terms are observed by sellers but not by researchers. This approach, combined with our full-solution estimation, directly addresses the endogeneity in prices.
5.2.2 Sales

Based on the utility function in Equation 3 and the error structure, the probability that consumers purchase from seller $j$ in market $m$ at time $t$, conditional on them making a purchase, can be expressed as:

$$P_{m,t}(\text{choosing } j \mid \text{choosing } k \in J_{m,t}) = \frac{\exp\left(\frac{\delta_{m,j,t}}{\rho}\right)}{\sum_{k \in J_{m,t}} \exp\left(\frac{\delta_{m,k,t}}{\rho}\right)}, \quad \forall j \in J_{m,t}.$$ 

The fraction of consumers who purchase the inside products can be written as:

$$P_{m,t}(\text{choosing } k \in J_{m,t}) = \frac{(D_{m,t})^\rho}{1 + (D_{m,t})^\rho},$$

where $D_{m,t} = \sum_{k \in J_{m,t}} \exp\left(\frac{\delta_{m,k,t}}{\rho}\right)$. The market share of seller $j$ in market $m$ at period $t$ can be represented as:

$$s_{m,j,t} = P_{m,t}(\text{choosing } j \mid \text{choosing } k \in J_{m,t}) \times P_{m,t}(\text{choosing } k \in J_{m,t}), \quad \forall j \in J_{m,t}.$$ 

The quantity of seller $j$ demanded by consumers in market $m$ at time $t$, $\tilde{q}_{m,j,t}$, follows a Poisson distribution:

$$\tilde{q}_{m,j,t} \sim \text{Poisson}(\lambda_{m,t} \times s_{m,j,t}), \quad \forall j \in J_{m,t}.$$ 

Note that the quantity demanded may not be equal to the actual sales that were observed in the data, as the sales may be limited by the remaining inventory of the seller. We can express seller $j$’s sales $q_{m,j,t}$ using the following equation:

$$q_{m,j,t} = \min\{\tilde{q}_{m,j,t}, \overline{q}_{m j,t}\}, \quad \forall j \in J_{m,t},$$

where $\overline{q}_{m,j,t}$ represents seller $j$’s remaining inventory in market $m$ at period $t$.

5.3 Seller Belief

We now turn to the supply side model. Based on the available data, each seller $j$ forms estimates of the current-period demand states for the seller itself and for its
competitor. If all sellers have complete access to the information and the necessary technology, the best possible estimates for the current-period demand states are denoted as \( h_{m,j,t}^{BP} \in \{0, 1\} \), and we discuss the derivation of these estimates in detail in Section 6.1. However, due to the possibility of heterogeneous calibrated belief among sellers, some noise is introduced, and therefore, the sellers’ beliefs about own demand state, which is a parameter between 0 and 1, follows

\[
\hat{h}_{m,j,t}^{Own} = \sum_{I \in \{0,1\}} I - \frac{\exp (\phi_0^{Own} + a(j) \times \phi_1^{Own})}{1 + \exp (\phi_0^{Own} + a(j) \times \phi_1^{Own})} \equiv p_{a(j)}^{Own} \times (I - h_{m,j,t}^{BP}).
\]

Here, \( p_{a(j)}^{Own} \in (0, 1) \) represents the accuracy of the seller’s belief about its own demand relative to the prediction, and depends on their identity \( a(j) \). When \( p_{a(j)}^{Own} \to 1 \), the seller’s belief is perfectly calibrated, meaning their beliefs align perfectly with \( h_{m,j,t}^{BP} \). When \( p_{a(j)}^{Own} \to 0 \), the seller’s belief is perfectly miscalibrated, meaning their beliefs are completely opposite to \( h_{m,j,t}^{BP} \). When \( p_{a(j)}^{Own} = 0.5 \), the seller perceives both states as equally likely. The parameter \( \phi_0^{Own} \) represents the baseline values for all sellers, while Amazon has an additional parameter value of \( \phi_1^{Own} \) on top of the baseline.

Similarly, the sellers’ beliefs about competitor’s state, which is also a parameter between 0 and 1, is defined as

\[
\hat{h}_{m,j,t}^{Competitor} = \sum_{I \in \{0,1\}} I - \frac{\exp (\phi_0^{Competitor} + a(j) \times \phi_1^{Competitor})}{1 + \exp (\phi_0^{Competitor} + a(j) \times \phi_1^{Competitor})} \equiv p_{a(j)}^{Competitor} \times (I - h_{m,j,t}^{BP}),
\]

where \( p_{a(j)}^{Competitor} \in (0, 1) \) represents the accuracy of seller’s belief about the competitor’s demand state relative to its prediction and depends on its identity \( a(j) \). \( \phi_0^{Competitor} \) represents the baseline parameter value that is shared among all sellers, including Amazon. If Amazon has a better calibrated belief about the competitor’s
demand state, $\phi_1^{\text{Competitor}}$, which is specific to Amazon, is expected to be positive in addition to the baseline.\(^\text{27}\)

The seller makes decisions to maximize their expected profits based on their beliefs. Similar to Equation 4, the seller’s belief is updated according to the following:

$$
\hat{\xi}_{m,j,t} = \varphi \times \hat{h}_{m,j,t}^{\text{Own}} + \nu_{m,j,t}.
$$

(5)

Sellers also form beliefs about their competitor’s demand intercept, denoted as $\tilde{\xi}_{m,-j,t}$, based on past observations and pricing decisions. The beliefs are updated according to the following equation:

$$
\hat{\xi}_{m,-j,t} = \varphi \times \hat{h}_{m,j,t}^{\text{Competitor}} + \nu_{m,-j,t}.
$$

(6)

Our model of seller beliefs is parsimonious. Given our main objective is to quantify the dependence between prices and past sales data, we choose to directly model this dependence without imposing a specific learning or belief formation process.

5.4 Profit Function and Pricing Decision

The sellers in the market can be classified into two types: third-party sellers $a(j) = 0$ and Amazon $a(j) = 1$. Among third-party sellers, there are variations in their demand functions and costs depending on whether they use Amazon’s fulfillment service. Amazon earns profits from its own sales and also charges fees to third-party sellers for using its platform to sell their products, including a referral fee, which is a percentage of the selling price. This referral fee is considered a cost for the third-party sellers.

\(^{27}\)One possible specification is to model $\hat{h}_{m,j,t}^{\text{Competitor}}$ as a function of $\hat{h}_{m,j,t}^{\text{Own}}$. For example, the value $\phi_0^{\text{Competitor}}$ differs depending on beliefs about own demand states, allowing seller $j$’s belief in the competitor’s demand state depending on belief of its own state. However, given that our primary interest is $p_{a(j)}^{\text{Competitor}}$, which measures the deviation of belief relative to the best prediction, we choose a more direct approach.
The profit function can be expressed as follows:

\[
\Pi_{m,j,t} = \begin{cases} 
(1 - r_m) \times p_{m,j,t} - mc_{m,j,t} \times q_{m,j,t}, & \text{if } a(j) = 0, \\
r_m \times p_{m,-j,t} \times q_{m,-j,t} + (p_{m,j,t} - mc_{m,j,t}) \times q_{m,j,t}, & \text{if } a(j) = 1, 
\end{cases}
\]

and seller \( j \)'s subjective profit function depends on its beliefs:

\[
\hat{\Pi}_{m,j,t} = \begin{cases} 
(1 - r_m) \times p_{m,j,t} - mc_{m,j,t} \times \hat{q}_{m,j,t}, & \text{if } a(j) = 0, \\
r_m \times p_{m,-j,t} \times \hat{q}_{m,-j,t} + (p_{m,j,t} - mc_{m,j,t}) \times \hat{q}_{m,j,t}, & \text{if } a(j) = 1, 
\end{cases}
\]

where \( r_m \) is the referral fee rate charged by Amazon as a proportion of the product price. The expected quantity sold by the seller \( j \) and its competitors in market \( m \) at time \( t \) are represented by \( \hat{q}_{m,j,t} \), respectively. The marginal cost of seller \( j \) is determined by a combination of its characteristics vector \( w \) and a cost shock \( \varsigma_{m,j,t} \) that follows a normal distribution. The cost function is expressed as:

\[
mc_{m,j,t} = w_{m,j,t}' \omega + \varsigma_{m,j,t}, \text{ where } \varsigma_{m,j,t} \sim N(0, \sigma_\varsigma^2).
\]

The supply shocks, denoted by \( \varsigma \), have a variance of \( \sigma_\varsigma^2 \) and a mean of zero. These shocks are observable to sellers but are unobserved by researchers. Sellers engage in a simultaneous move pricing game to make their pricing decisions.\(^{28}\) We consider the equilibrium Nash pricing in each period, allowing for a flexible belief regarding own and competitors’ demand states.

**Model Discussion** To conclude, we discuss several assumptions embedded within the supply model. First, FBA sellers incur an additional per-unit fulfillment fee on top of the standard referral fee. The per-unit fee is constant for each product and unlike referral fee, it does not change depending on prices. Therefore, the per-unit fee is implicitly captured in the marginal cost for FBA sellers. We assume that Amazon’s

\(^{28}\)This simultaneity aligns with the institutional setup, as nearly all leading providers of automated pricing offer instant repricing (see the repricing frequency survey in Appendix E).
cost of fulfilling the FBA order is equivalent to the revenue derived from fees, and therefore, the model does not consider Amazon’s profit in the FBA segment.

Second, following canonical supply models, we do not explicitly model a “decision” or cost of repricing. If a seller does not reprice, our model would rationalize this behavior using a marginal cost $c_{m,j,t}$. We assume that, on average, heuristics in pricing algorithms align with profit-maximizing incentives.\textsuperscript{29}

Third, we abstract from optimally setting referral fees, as Amazon is known for rarely changing them. Lastly, Amazon has many tools for information design aimed at consumers, such as product recommendations, search ranking, and the buy box. These tools may interact with seller types (i.e., Amazon vs. non-Amazon) as shown by the current empirical literature cited in Section 1.1. We focus on price competition and information design for sellers and treat other effects as fixed in the counterfactual analyses. The study of their interactions is left for future work.

6 Estimation and Identification

We apply the structural model to the data and obtain model estimates. The demand primitives includes both static preference parameters and dynamic preference parameters:

$$
\theta^D = \left\{ \{\alpha, \rho, \beta\}, \{\varphi, \sigma_\nu\} \right\}.
$$

The seller primitives include the marginal cost and the parameters related to how

\textsuperscript{29}Sellers may adopt pricing heuristics, assumed to align with profit-maximizing motives. This profit-maximizing assumption might be considered more suitable than modeling specific and exact heuristics because sellers may select varying heuristic rules based on different, unobserved circumstances that researchers cannot observe. While these heuristics are endogenous and may change in the counterfactual, the underlying profit-driven incentive is likely to remain consistent.
sellers learn from past sales:

$$\theta^S = \{\omega, \sigma, \phi_{\text{Own}}, \phi_{\text{Competitor}}\}.$$  

6.1 Estimation

Below, we provide a detailed description of the estimation procedure. We then discuss the identification of key parameters in the estimation process.

Use Data Neighboring Repricing Events  We construct a balanced panel to capture within-product price variations in a concise 3-day timeframe surrounding repricing events. These events are characterized by price adjustments taking place on day $t$, while no adjustments occur on the preceding or subsequent days. Formally, the set of repricing events is defined as follows:

$$S_{\text{repricing}} = \{S(m,j,t) \in \mathbb{N} \mid p_{m,j,t} \neq p_{m,j,t-1} \land p_{m,j,t+r} = p_{m,j,t+r-1}, \quad \forall r \in \{-1, 1\}\}.$$  

The dataset for estimation includes the sales and prices of the repricing seller and its competitor for both the day before and the day after the repricing event, denoted as $\tilde{t} = -1$ and $\tilde{t} = 1$, respectively. To focus on within-product price variation, we normalize price by the mean price of each product and set the average price across the sample to be $70$.

Model Specification  We discuss how we model demand and supply heterogeneities. Depending on the types of sellers (i.e., Amazon [AMZ], Fulfillment by Amazon [FBA], and Fulfillment by Merchant [FBM]) present in a market, we can have five possible market structures:

$$\mathcal{M} (m) \in \{\text{AMZ-vs-FBM, AMZ-vs-FBA, FBA-vs-FBM, FBA-vs-FBA, FBM-vs-FBM}\}.$$
We allow each of these market types to have different utility intercepts, marginal costs, variances of demand shocks, and variances of cost shocks.\(^{30}\) Note that the seller types are ordered and some types of markets have asymmetric seller types. We further allow for within-market heterogeneity by permitting this asymmetry in both utility intercepts and marginal costs. We also include a cost shock, denoted as \(\omega_{\text{Post}}\), for the period after the repricing event.

**True Demand States** We use the following regression to estimate the demand states that explain the sales after incorporating the effect of prices and product-seller fixed effects:\(^{31}\)

\[
q_{m,j,t} = \eta \times p_{m,j,t} + \psi_{m,j} + \epsilon_{m,j,t}. \tag{8}
\]

We include the product-seller fixed effects, denoted by \(\psi_{m,j}\), to account for unobserved and observed heterogeneity across each product listing. By doing so, the demand state is defined by the variation in demand within a listing. To remove sales variation shifted by prices, we use the log of inventory as an instrument for the price. The inventory level acts as a cost shifter since sellers may face higher costs when they have excess inventory due to storage costs (see Appendix H).

We discretize the true demand states for later structural estimation. We define the demand states \(h_{m,j,t}\) as a higher state \((h_{m,j,t} = 1)\) when the residuals from Equation 8 (i.e., \(\hat{\epsilon}_{m,j,t}\)) are greater than the median of the residuals. Alternatively, the demand states are considered to be in a lower state \((h_{m,j,t} = 0)\) when the residuals are less than or equal to the median of the residuals. All medians are computed within the

\(^{30}\)In the utility function, we include \(\beta_{\text{AMZ,FBA}}\) and \(\beta_{\text{AMZ,FBM}}\) to denote the utility intercept of Amazon relative to FBA or FBM sellers, respectively, and \(\beta_{\text{FBA,FBM}}\) to denote the utility intercept of FBA sellers relative to FBM sellers. In the cost function, we include \(\omega_{\text{AMZ,FBA}}\) and \(\omega_{\text{AMZ,FBM}}\) to measure the average difference in cost between Amazon and FBA or FBM sellers, respectively, and \(\omega_{\text{FBA,FBM}}\) to measure the average difference in cost between FBA and FBM sellers.

\(^{31}\)See Kalouptsidis (2014) and Jeon (2022) for a similar approach to constructing demand state when modeling demand uncertainty.
same market structure and seller types. Formally, we have:

\[ h_{m,j,t} = \begin{cases} 
1, & \text{if } \hat{\epsilon}_{m,j,t} > \text{median} \left( \hat{\epsilon}_{m',j',t} \mid M(m') = M(m), a(j') = a(j) \right), \\
0, & \text{if } \hat{\epsilon}_{m,j,t} \leq \text{median} \left( \hat{\epsilon}_{m',j',t} \mid M(m') = M(m), a(j') = a(j) \right). 
\]

**Best Predicted Demand States**

Sellers can use past states to predict the current state, since demand exhibits autocorrelation (see Appendix G.3.1). We aggregate all past sales information into a simple statistic called ex-ante best predicted demand state. Note that true demand states are estimated using ex-post sales, which are unavailable to sellers when setting price. To estimate the ex-ante best predicted demand states, we use past demand states of the sellers’ own sales and those of their competitors:

\[ h_{m,j,t} = \sum_{\tau = -T}^{-1} \kappa_{\tau,j} \times h_{m,j,\tau} + \sum_{\tau = -T}^{-1} \kappa_{\tau,-j} \times h_{m,-j,\tau} + \epsilon_{m,j,t}. \] (9)

In practice, we choose \( T = -7 \), which corresponds to using demand states from the previous week. Extending the timeframe beyond a week has minimal effect on prediction accuracy. Similarly, we discretize the best predicted demand states. We define the best predicted demand state as a higher state \( h_{BP,m,j,t} = 1 \) when the predicted value \( \hat{h}_{m,j,t} \) in Equation 9 is greater than its median, and a lower state \( h_{BP,m,j,t} = 0 \) otherwise. As before, all medians are computed within the same market structure and seller types. Formally, we have:

\[ h_{BP,m,j,t} = \begin{cases} 
1, & \text{if } \hat{h}_{m,j,t} > \text{median} \left( \hat{h}_{m',j',t} \mid M(m') = M(m), a(j') = a(j) \right), \\
0, & \text{if } \hat{h}_{m,j,t} \leq \text{median} \left( \hat{h}_{m',j',t} \mid M(m') = M(m), a(j') = a(j) \right). 
\]

Using this approach, we find that the ex-post true demand state \( h_{m,j,t} \) and the ex-ante best predicted one \( h_{BP,m,j,t} \) coincide 79.21% of the time, indicating that past sales data plays a significant role in predicting the current demand state.\textsuperscript{32} Note that in

\textsuperscript{32}We use the term “best predicted demand states” to refer to demand information extracted from historical sales. However, the term should not be interpreted as literal truths or ultimate predictions. In practice, we also consider and allow additional demand information through the error term \( \nu_{m,j,t} \).
practice $h_{m,j,t}^{BP}$ and $h_{m,-j,t}^{BP}$ are correlated, given the structure described in Equation 9.

**Inner Loop**  Let the vector of demand and supply primitives be $\theta = \{\theta^D, \theta^S\}$. As the demand shocks $\nu$ and cost shocks $\varsigma$ are unobservable in a given observation, we use a Hermite-Gauss quadrature of order 3 to simulate four normally distributed variables representing demand and cost shocks for both the seller and its competitor. This results in a total of 81 possible joint distributions of demand and cost shocks. To solve for equilibrium outcomes, including prices and sales, we simultaneously solve for demand and supply for each joint shock distribution. We approximate these outcomes using the Hermite-Gauss quadrature weights assigned to each joint distribution.

There are 16 possible states resulting from the combination of a seller’s and its competitor’s demand states ($h_j$ and $h_{-j}$, respectively), as well as their respective best predicted demand states ($h_{j}^{BP}$ and $h_{-j}^{BP}$). We solve for equilibrium in each of the five market structures, both before and after the day of repricing, across the 16 demand states and $3^4 = 81$ joint distributions of demand shocks and cost shocks. Thus, we solve equilibria for 12,960 pricing games during each iteration.

**Outer Loop**  In the outer loop, we use a simulation estimator to match predicted moments from the model to observed moments in the data one day (i.e., $\tilde{t} \in \{-1, 1\}$) neighboring repricing events $S_{\text{repricing}}$. We utilize the following moments.

1. Own price and sales (320 moments):

   $$E \left[ p_{m,j}^{\tilde{t}} \times z_{m,j}^{\tilde{t}} \right] \text{ and } E \left[ q_{m,j}^{\tilde{t}} \times z_{m,j}^{\tilde{t}} \right],$$

2. Higher order price moments: the square of own price and the interaction with competitor’s price (320 moments):

   $$E \left[ p_{m,j}^{\tilde{t}}^2 \times z_{m,j}^{\tilde{t}} \right] \text{ and } E \left[ p_{m,j}^{\tilde{t}} \times p_{d,-j}^{\tilde{t}} \times z_{m,j}^{\tilde{t}} \right],$$
3. The interaction of own price with own sales and competitor’s sales (320 moments):

\[ E[p_{m,j,i} \times q_{m,j,i} \times z_{m,j,i}] \quad \text{and} \quad E[p_{m,j,i} \times q_{d,-j,i} \times z_{m,j,i}] \].

The vector of 160 indicators \( z_{m,j,i} \) is defined as (see Appendix I for a detailed breakdown of these vectors):

\[
 z_{m,j,i} = \underbrace{M_{m,j,i}}_{\text{market structures (5×1)}} \otimes \underbrace{H_{m,j,i}}_{\text{predicted and true demand states (16×1)}} \otimes \underbrace{T_{m,j,i}}_{\text{before and after repricing (2×1)}}.
\]

In total, we have 34 model primitives. Denote the vector of empirical moments as \( \phi \) and a vector of simulated moments as \( \phi(\theta) \). Given a weighting matrix \( W \), the outer loop minimizes the following objective function:

\[
 f(\theta) = \left[ \hat{\phi}(\theta) - \phi \right]' W \left[ \hat{\phi}(\theta) - \phi \right].
\]

In practice, we use the weighting matrix \( W \) to normalize the scales of the moments. Standard errors are obtained using a sandwich formula.

### 6.2 Identification

We begin our discussion by examining the identification of price elasticity. To do this, we take advantage of the high-frequency data available to us. We construct a balanced panel that captures within-product price variations within a concise 3-day timeframe. Our assumption is that, during this brief period, the underlying demand remains stable. We then attribute high-frequency fluctuations in prices to two supply-side factors: a common shock in marginal cost (\( \omega_{Post} \)) as well as variations in beliefs. Following the literature, we acknowledge that sellers may possess superior information compared to researchers by allowing for both demand and supply shocks that are observable to sellers but not to the researchers. Given the sparsity of sales data, it is not feasible to directly invert demand shocks. Instead, we employ a full
solution approach that simultaneously solves the demand and supply models, taking into account the unobserved demand and supply shocks.

To identify the variance of demand shocks, we focus on the covariance between price and sales. Specifically, for a given price, observed sales may deviate from what is expected based on price elasticity. We attribute the distribution of these residual demands to the distribution of demand shocks. In contrast, supply shocks are independent of residual demand but still contribute to price shifts. After determining the distribution of demand shocks, we can use the variance of supply shocks to rationalize the distribution of prices, which we capture by employing the square of price as a moment.

The parameter $\varphi$ is identified by the difference in average sales under high demand states relative to low demand states. Given the value of $\varphi$, we infer sellers’ beliefs from their pricing levels (e.g., Aguirregabiria, 2021) specifically, the learning parameters can be identified through the dependence of prices on past sales. In particular, a higher value of $\phi^{\text{Own}}$ indicates that seller $j$ sets higher prices when $h_{j}^{\text{BP}} = 1$ compared to when $h_{j}^{\text{BP}} = 0$. Meanwhile, a higher value of $\phi^{\text{Competitor}}$ suggests that seller $j$ adjusts its price in response to $h_{-j}^{\text{BP}}$. Based on our reduced-form findings, which demonstrate that Amazon sets its prices according to competitor demand state while third-party sellers do not, we expect to observe a higher value of $\phi_{1}^{\text{Competitor}}$ and a lower value of $\phi_{0}^{\text{Competitor}}$.

7 Results

In Figure 4, we assess the fit of our model by comparing the empirical and predicted prices and sales. The model adequately explains the sales and prices observed in the data.

Columns 1 to 3 of Table 2 display the demand estimates. The average own-price elasticity is $-18.96$, a magnitude consistent with previous literature (e.g., Ellison
Figure 4: Moment Fit

Note: Figure 4 evaluates the moment fit, with the x-axis representing the empirical moment and the y-axis representing the model prediction. The moments are aggregated at the market-type×seller level. The fit of the price moment is shown in Figure 4a, while the fit of the sales moment is presented in Figure 4b.

and Ellison, 2009; Dinerstein et al., 2018). This high own-price elasticity primarily stems from the intense competition between two sellers offering the same product on a shared product page. The cross-price elasticity, at 18.41, is high as expected, but remains lower than what a classic Bertrand model would predict. The average market price elasticity, at −5.28, reflects the level of competition against the outside option. Based on the estimates, competition across listings within the same product is notably more intense than that against the outside option.

Consumers derive greater utility from purchasing products from Amazon or FBA sellers than FBM sellers. Note that we normalize the price to $70 in the model; the estimated premiums over FBM sellers are $7.15 and $6.12 respectively, and in AMZ-vs-FBA markets, consumers experience an estimated gain of $5.31 when buying from Amazon rather than from an FBA seller. The estimate of \( \varphi \) on the true demand
state reveals that demand indeed fluctuates over time, as indicated by its positive and significant value.

Columns 4 to 6 of Table 2 display the supply estimates. In the same market, both Amazon and FBA sellers exhibit lower marginal costs than FBM sellers, with cost advantages of $1.81 and $8.77, respectively. In the AMZ-vs-FBA market, Amazon’s marginal cost is $14.72 higher compared to FBA sellers. This difference mainly reflects the nature of FBA sellers, who are mostly professionals offering more competitive prices.

The parameters $\phi_{own}$ and $\phi_{competitor}$ represent the degree to which sellers’ beliefs align with the best predicted demand states $h^{BP}_j$ and $h^{BP}_j$ based on their own and competitors’ past sales. Based on the $\phi_{own}$ parameter estimates, both Amazon and third-party sellers have well-calibrated beliefs on their own demand states. Their accuracy levels are similar, though Amazon’s is slightly better, aligning more closely with its own $h^{BP}$ at $p^{own}_1 = 0.98$, compared to third-party sellers’ $p^{own}_0 = 0.92$.

Regarding belief of competitors’ demand states, Amazon’s belief closely aligns with the competitor’s $h^{BP}$, as indicated by $p^{competitor}_1 = 0.94$. In contrast, third-party sellers’ beliefs closely resemble a random guess, with $p^{competitor}_0 = 0.52$.

Overall, our structural estimations rationalize the reduced-form patterns we observed in Section 4 with a rational framework of price competition and heterogeneous beliefs. Specifically, our estimates indicate that Amazon possesses a better-calibrated belief parameter, especially in learning from competitors’ sales. This finding highlights the information advantage held by Amazon and the consequent disadvantage faced by third-party sellers.

### 7.1 Counterfactual Simulations

We conduct two counterfactual analyses, corresponding to proposals that Amazon put forward in response to EU antitrust investigations, to examine the impact of information advantage on price competition. These proposals involve (1) preventing
Table 2: Parameter Estimates

<table>
<thead>
<tr>
<th>Demand Parameters</th>
<th>Estimate</th>
<th>SE</th>
<th>Supply Parameters</th>
<th>Estimate</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>7.97</td>
<td>(0.12)</td>
<td>$\omega_{\text{AMZ,FBM}}$</td>
<td>-1.81</td>
<td>(0.15)</td>
</tr>
<tr>
<td>$\beta_{\text{AMZ,FBM}}$</td>
<td>0.57</td>
<td>(0.02)</td>
<td>$\omega_{\text{AMZ,FBA}}$</td>
<td>14.72</td>
<td>(0.20)</td>
</tr>
<tr>
<td>$\beta_{\text{AMZ,FBA}}$</td>
<td>0.42</td>
<td>(0.02)</td>
<td>$\omega_{\text{FBA,FBM}}$</td>
<td>-8.77</td>
<td>(0.23)</td>
</tr>
<tr>
<td>$\beta_{\text{FBA,FBM}}$</td>
<td>0.49</td>
<td>(0.03)</td>
<td>$\omega_{\text{Post}}$</td>
<td>2.27</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Intraclass Correlation $\rho$</td>
<td>0.15</td>
<td>(0.01)</td>
<td>$\phi_{0}^{\text{own}}$: Baseline</td>
<td>2.38</td>
<td>(0.15)</td>
</tr>
<tr>
<td>$\varphi$</td>
<td>3.07</td>
<td>(0.03)</td>
<td>$\phi_{0}^{\text{own}}$: Amazon</td>
<td>1.67</td>
<td>(0.37)</td>
</tr>
<tr>
<td>Market Structure FE</td>
<td></td>
<td></td>
<td>$\phi_{0}^{\text{competitor}}$: Baseline</td>
<td>0.09</td>
<td>(0.01)</td>
</tr>
<tr>
<td>AMZ-vs-FBM</td>
<td>-3.53</td>
<td>(0.09)</td>
<td>$\phi_{1}^{\text{competitor}}$: Amazon</td>
<td>2.63</td>
<td>(0.14)</td>
</tr>
<tr>
<td>FBA-vs-FBM</td>
<td>-1.95</td>
<td>(0.08)</td>
<td>Market Structure FE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FBA-vs-FBM</td>
<td>-0.41</td>
<td>(0.08)</td>
<td>AMZ-vs-FBM</td>
<td>55.34</td>
<td>(0.13)</td>
</tr>
<tr>
<td>FBM-vs-FBM</td>
<td>-5.20</td>
<td>(0.26)</td>
<td>FBA-vs-FBM</td>
<td>57.38</td>
<td>(0.16)</td>
</tr>
<tr>
<td>AMZ-vs-FBA</td>
<td>-1.77</td>
<td>(0.08)</td>
<td>FBA-vs-FBA</td>
<td>53.16</td>
<td>(0.14)</td>
</tr>
<tr>
<td>$\sigma_v$</td>
<td></td>
<td></td>
<td>FBM-vs-FBM</td>
<td>51.87</td>
<td>(0.12)</td>
</tr>
<tr>
<td>AMZ-vs-FBM</td>
<td>0.56</td>
<td>(0.06)</td>
<td>AMZ-vs-FBA</td>
<td>47.89</td>
<td>(0.14)</td>
</tr>
<tr>
<td>FBA-vs-FBM</td>
<td>0.20</td>
<td>(0.18)</td>
<td>$\sigma_c$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FBA-vs-FBM</td>
<td>0.06</td>
<td>(0.28)</td>
<td>AMZ-vs-FBM</td>
<td>16.52</td>
<td>(0.10)</td>
</tr>
<tr>
<td>FBM-vs-FBM</td>
<td>2.66</td>
<td>(0.14)</td>
<td>FBA-vs-FBM</td>
<td>2.99</td>
<td>(1.25)</td>
</tr>
<tr>
<td>AMZ-vs-FBA</td>
<td>0.14</td>
<td>(0.06)</td>
<td>FBA-vs-FBA</td>
<td>0.58</td>
<td>(2.24)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>FBM-vs-FBM</td>
<td>15.01</td>
<td>(0.19)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>AMZ-vs-FBA</td>
<td>2.69</td>
<td>(1.02)</td>
</tr>
</tbody>
</table>

Note: Table 2 displays the parameter estimates. Standard errors in parentheses are clustered at the nest level. The price coefficient $\alpha$ is scaled by a factor of 100, while we normalize price by the mean price of each product and set the average price across the sample to be $70. We allow four parameters to differ across five market structure: (1) AMZ-vs-FBM, where Amazon competes with an FBM seller, (2) FBA-vs-FBM, where an FBA seller competes with an FBM seller, (3) FBA-vs-FBA, where two FBA sellers compete with each other, (4) FBM-vs-FBM, where two FBM sellers compete with each other, and (5) AMZ-vs-FBA, where Amazon competes with an FBA seller. We convert each repricing adjustment into a price-increasing event, so the cost shock $\omega_{\text{Post}}$ is positive.
Amazon from using marketplace data for its own retail business and (2) sharing marketplace data with third-party sellers. To highlight the role of the vertically integrated market structure, we also vary the referral fee and examine how it mediates the effect. Detailed information regarding the welfare calculation can be found in Appendix J.

7.1.1 Restricting Information Advantage

In the first counterfactual scenario, Amazon loses its information advantage because it is prevented from using marketplace data for its pricing decision.\textsuperscript{33} To simulate this, we set Amazon’s learning parameter $p_{1}^{\text{competitor}}$ equal to that of third-party sellers $p_{0}^{\text{competitor}}$. The results in Columns 1 to 3 of Table 3 show that, under the current 15% referral fee and restricted information access for Amazon, Amazon’s sales decrease and profits decrease by 0.64% and 0.30%, respectively, while third-party sellers experience a 2.63% increase in sales and a 2.36% profit gain. While more information increases efficiency, the superior information also grants market power, allowing the advantaged party better discern when to raise prices. This leads to an anti-competitive effect that outweighs the efficiency gains. Consequently, by removing the information advantage and thus the market power associated with it, the average price decreases, leading to improvements in consumer welfare and social welfare by 0.48% and 0.33%, respectively.\textsuperscript{34}

We further emphasize the role of vertical market structure in our findings by examining the scenario where Amazon charges a 0% referral fee, eliminating vertical

\footnotesize
\textsuperscript{33}This is similar to the settlement reached between Amazon and the EU, which concerns Amazon’s internal structural data separation between its platform business and retail business. The final settlement can be found at https://ec.europa.eu/commission/presscorner/detail/en/ip_22_7777. See Section 2 for more discussion.

\textsuperscript{34}In theory, the equilibrium price of the advantaged party may increase or decrease when the information advantage is removed. For instance, in the AMZ-vs-FBA market, where Amazon may possess less market power due to the cost difference, the average price increases.
Columns 4 to 6 of Table 3 display the changes in equilibrium outcomes when Amazon has no information advantage, compared to the case with Amazon’s information advantage under a 0% referral fee. Amazon’s sales and profits drop significantly by 4.61% and 4.68%, respectively. Conversely, third-party sellers experience substantial increases in sales and profits, at 7.27% and 7.26%, respectively. The average increase in consumer welfare and social welfare across the two markets is approximately 0.48% and 0.61%, respectively. The larger effect under a 0% referral fee compared to a 15% referral fee indicates that, in the absence of vertical incentives, market power stemming from informational advantage may pose a more prominent concern.

### 7.1.2 Sharing Information

In the second counterfactual, we explore a scenario in which Amazon shares its marketplace data with third-party sellers, thereby eliminating their information disadvantage. We simulate this situation by granting third-party sellers the same access to information and learning parameters as Amazon. Specifically, we let $p_{0}^{\text{competitor}} = p_{1}^{\text{competitor}}$.  

Columns 1 to 3 of Table 4 present the results for this counterfactual, assuming the current 15% referral fee remains in place. Our findings indicate a substantial increase of 14.91% in sales for third-party sellers, while Amazon’s sales experience a 4.08% decline. Moreover, information sharing leads to a more substantial rise in consumer welfare and social welfare on average, with estimated increases of 2.08% and 1.65%, respectively.

---

35 This scenario addresses information design in the context of structural separation, where Amazon, as the retailer, does not collect fees from sellers (i.e., separating the platform-Amazon from the retailer-Amazon).  
36 We assume that third-party sellers can use competitors’ sales information to infer competitors’ demand state, similar to Amazon. This assumption is supported by our model estimates, which demonstrate that third-party sellers have beliefs about their own demand state comparable to Amazon’s when using their own sales information.
Table 3: Counterfactual Analysis of Restricting Amazon’s Information Advantage

<table>
<thead>
<tr>
<th></th>
<th>15% Referral Fee</th>
<th>0% Referral Fee</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AMZ-vs-FBM</td>
<td>AMZ-vs-FBA</td>
</tr>
<tr>
<td>%Δ Amazon Price</td>
<td>-0.27</td>
<td>0.34</td>
</tr>
<tr>
<td>%Δ Amazon Sales</td>
<td>0.08</td>
<td>-7.86</td>
</tr>
<tr>
<td>%Δ 3rd-Party Price</td>
<td>-0.13</td>
<td>-0.04</td>
</tr>
<tr>
<td>%Δ 3rd-Party Sales</td>
<td>2.37</td>
<td>5.24</td>
</tr>
</tbody>
</table>

Panel A: Equilibrium Outcomes

Panel B: Profit and Welfare Change

|                              | AMZ-vs-FBM       | AMZ-vs-FBA      | AMZ-Average | AMZ-vs-FBM | AMZ-vs-FBA | AMZ-Average |
| %Δ Amazon Profit             | -0.30            | -0.34           | -0.30       | -2.18      | -29.73     | -4.68       |
| %Δ 3rd-Party Profit          | 1.94             | 6.52            | 2.36        | 5.99       | 19.99      | 7.26        |
| %Δ Consumer Welfare          | 0.58             | -0.58           | 0.48        | 0.46       | 0.74       | 0.48        |
| %Δ Social Welfare            | 0.30             | 0.69            | 0.33        | 0.33       | 3.42       | 0.61        |

Note: Table 3 presents the counterfactual analysis when Amazon’s information is restricted. Panel A shows the percentage changes in equilibrium prices and sales, while Panel B quantifies the changes in profits and welfare for Amazon, third-party sellers, and consumers. AMZ-vs-FBM represents the market where Amazon competes with an FBM seller. AMZ-vs-FBA represents the market where Amazon competes with an FBA seller. AMZ-Average represents the average change weighted by the number of observations across both markets, AMZ-vs-FBM and AMZ-vs-FBA. Columns 1 to 3 correspond to the current 15% referral fee, and Columns 4 to 6 correspond to the case when the referral fee is reduced to 0%.
respectively. With increased information being shared, prices better reflect demand states and improve the matching quality of supply and demand. This results in a slight decrease in average prices but a significant increase in overall output. Consumers and third-party sellers benefit greatly, and Amazon indirectly gains from market expansion through referral fees.\footnote{This finding underscores the role of referral fees in aligning the owner’s incentives to share information and is consistent with recent observations regarding Amazon’s information sharing (see Appendix B). Columns 4 to 6 of Table 4 present the results for the counterfactual where third-party sellers possess equal information as Amazon, compared to the scenario in which they are information disadvantaged under a 0\% referral fee. In this scenario, Amazon’s average profit decreases by 5.66\%, driven by the loss of first-party sales without generating any referral revenue.}

Comparing the two counterfactuals, sharing information yields a greater social welfare gain than restricting information, despite a lesser average price reduction in the former. This gain mainly comes from the increased information enhancing the matching quality of supply and demand.

**Markets with Only Third-Party Sellers** Information sharing among third-party sellers can also influence markets where these sellers compete with one another, and Amazon does not function as a seller. The counterfactual results for this scenario are explained in detail in Appendix K.

**All Types of Markets** In summary, when considering all market types, including those with only third-party sellers, in our dataset and using their empirical weights, the implementation of information sharing leads to a significant improvement in both consumer welfare and social welfare, with respective increases of 4.02\% and 2.39\% when the referral fee is set at the current level of 15\%.

To put the numbers into context, each number represents the daily welfare change for an average product in the data, with the average consumer welfare and social welfare being $3.19 and $6.72 per product each day. For every one million products
Table 4: Counterfactual Analysis of Sharing Information with Third-Party Sellers

<table>
<thead>
<tr>
<th></th>
<th>15% Referral Fee</th>
<th></th>
<th></th>
<th>0% Referral Fee</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AMZ-vs-FBM</td>
<td>AMZ-vs-FBA</td>
<td>AMZ-Average</td>
<td>AMZ-vs-FBM</td>
<td>AMZ-vs-FBA</td>
<td>AMZ-Average</td>
</tr>
<tr>
<td><strong>Panel A: Equilibrium Outcomes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%Δ Amazon Price</td>
<td>0.01</td>
<td>-0.17</td>
<td>-0.01</td>
<td>-0.93</td>
<td>-0.90</td>
<td>-0.93</td>
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<tr>
<td>%Δ Amazon Sales</td>
<td>-1.80</td>
<td>-27.01</td>
<td>-4.08</td>
<td>-0.58</td>
<td>-24.53</td>
<td>-2.75</td>
</tr>
<tr>
<td>%Δ 3rd-Party Price</td>
<td>-0.12</td>
<td>-0.02</td>
<td>-0.11</td>
<td>-1.02</td>
<td>-0.62</td>
<td>-0.98</td>
</tr>
<tr>
<td>%Δ 3rd-Party Sales</td>
<td>12.51</td>
<td>39.00</td>
<td>14.91</td>
<td>16.76</td>
<td>33.43</td>
<td>18.27</td>
</tr>
<tr>
<td><strong>Panel B: Profit and Welfare Change</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%Δ Amazon Profit</td>
<td>0.05</td>
<td>4.48</td>
<td>0.45</td>
<td>-3.33</td>
<td>-29.01</td>
<td>-5.66</td>
</tr>
<tr>
<td>%Δ 3rd-Party Profit</td>
<td>2.84</td>
<td>19.87</td>
<td>4.38</td>
<td>2.25</td>
<td>11.82</td>
<td>3.12</td>
</tr>
<tr>
<td>%Δ Consumer Welfare</td>
<td>1.31</td>
<td>9.82</td>
<td>2.08</td>
<td>4.38</td>
<td>14.45</td>
<td>5.29</td>
</tr>
<tr>
<td>%Δ Social Welfare</td>
<td>0.88</td>
<td>9.41</td>
<td>1.65</td>
<td>1.64</td>
<td>8.87</td>
<td>2.29</td>
</tr>
</tbody>
</table>

Note: Table 4 presents the counterfactual analysis when Amazon shares its information with third-party sellers. Panel A shows the percentage changes in equilibrium prices and sales, while Panel B quantifies the changes in profits and welfare for Amazon, third-party sellers, and consumers. AMZ-vs-FBM represents the market where Amazon competes with an FBM seller. AMZ-vs-FBA represents the market where Amazon competes with an FBA seller. AMZ-Average represents the average change weighted by the number of observations across both markets, AMZ-vs-FBM and AMZ-vs-FBA. Columns 1 to 3 correspond to the current 15% referral fee, and Columns 4 to 6 correspond to the case when the referral fee is reduced to 0%.
similar to those in our dataset that are sold over a one-year period, the resulting increase in consumer welfare and social welfare would amount to approximately $46.81 million ($3.19 \times 365 \times 4.02\%) and $58.62 million ($6.72 \times 365 \times 2.39\%)$, respectively. However, we suggest interpreting these numbers with caution, mindful of the numerous simplifications made in our model. Among these is the fact that Amazon carries a wide array of products. How multiproduct pricing interacts with informational advantage and impacts Amazon’s market power could present an interesting avenue for future research.

8 Conclusion

This research examines the impact of asymmetric information access on price competition in a vertically integrated platform. We identify empirical patterns wherein individual sellers gain insights into demand through their own sales, while the platform owner has access to competitor sales data, enabling it to better understand demand and set prices. We estimate a structural model to quantify the importance of information advantage. Counterfactual analysis shows a significant impact of information access design on equilibrium outcomes and efficiency, highlighting information advantage as a potential source of market power.

We note that the information-advantage-induced market power we quantify likely represents a lower bound for the following reasons: first, the platform owner may have more information than sales data, for example, personalized data and search data, which may also contribute to a greater extent of information advantage. Second, the owner’s information advantage may interact with other platform designs such as product recommendations. One could argue that this interaction would further increase the platform owner’s market power.

There are numerous types of data with many other uses in various contexts. For example, sales data can inform entry and exit decisions, whereas search data can be
used to understand consumer preferences. While the data is non-rivalrous, the market is not. Our findings highlight the equilibrium effect of data access in a competitive setting, particularly concerning the impact of past sales data on price competition. However, we believe that this topic has broader implications and contains several avenues for further research.
References


Appendix

The appendix is intended for online publication.

A Theoretical Model

The demand system for two firms, 1 and 2, in a duopoly is described below:

\[ q_1 = A_1 - k_1 A_2 - a_1 p_1 + b_1 p_2, \quad q_2 = A_2 - k_2 A_1 - a_2 p_2 + b_2 p_1. \]

Assuming that firm 1 charges a referral fee \( 0 < r < 1 \) from firm 2, the profit functions of both firms are presented below.

\[ \pi_1 = p_1 q_1 + r p_2 q_2, \quad \pi_2 = (1 - r) p_2 q_2, \]

The parameters \( k, a, b \) and \( r \) are positive deterministic numbers and it is assumed that a firm’s own price has a greater impact on demand than its competitor’s price \((a_1 > b_1 \text{ and } a_2 > b_2)\). Moreover, we assume a firm’s price has a greater impact on its own demand than its competitors’ demand \((a_2 > b_1 \text{ and } a_1 > b_2)\). We simplify the model by assuming that firms have zero marginal costs. Price and quantity must be non-negative.

The firm-specific demand shocks, \( A_1 \) and \( A_2 \), are positive and distributed according to cumulative distribution functions \( F(A_1) \) and \( F(A_2) \), with corresponding density functions \( f(A_1) \) and \( f(A_2) \), respectively. The parameters \( k_1 \) and \( k_2 \) are less than 1 and \( \eta_{A_j} \) denotes the mean of \( A_j \), \( \forall j \in (1, 2) \). These distributions are common knowledge to both firms.

As a benchmark, we consider the current situation where Firm 1 has an information advantage over Firm 2, knowing both \( A_1 \) and \( A_2 \), while Firm 2 only knows \( A_2 \). We then explore two scenarios:

1. Perfect Information: Both firms have full information on both \( A_1 \) and \( A_2 \). 

2. Limited Information: Each firm is only aware of its own $A$ value, with Firm 1 knowing $A_1$ and Firm 2 knowing $A_2$. 

### A.1 Benchmark: Information Advantage

We begin by analyzing the model under the information advantage benchmark, where Firm 1 has knowledge of both $A_1$ and $A_2$, while Firm 2 is aware only of $A_2$. The prices and sales, $p$ and $q$, respectively, are as follows:

\[
p_1^A = \frac{2A_1a_2 - \eta A_1 k_2 (b_1 + rb_2) + A_2 (b_1 - 2a_2 k_1 + rb_2)}{4a_1a_2 - b_2 (b_1 + rb_2)} \geq 0,
\]

\[
p_2^A = \frac{-2a_1 A_2 - A_1 b_2 + A_2 b^2 k_1 + 2a_1 \eta A_1 k_2}{-4a_1a_2 + b_2 (b_1 + rb_2)} \geq 0.
\]

\[
q_1^A = \frac{b_2 (-A_1 + A_2 k_1) rb_2 + a_1 (2A_1a_2 + A_2 (b_1 - 2a_2 k_1 - rb_2) + \eta A_1 k_2 (-b_1 + rb_2))}{4a_1a_2 - b_2 (b_1 + rb_2)} \geq 0,
\]

\[
q_2^A = \frac{a_2 (2a_1 A_2 + A_1 b_2 - A_2 b^2 k_1 - 2a_1 \eta A_1 k_2)}{4a_1a_2 - b_2 (b_1 + rb_2)} - (A_1 - \eta A_1) k_2 \geq 0.
\]

The expected profits for Firm 1 and Firm 2 can be defined as follows:

\[
\mathbb{E}[\Pi_1^A] = \int_{A_2} \int_{A_1} p_1^A q_1^A dF(A_1) dF(A_2), \quad \mathbb{E}[\Pi_2^A] = \int_{A_2} \int_{A_1} p_2^A q_2^A dF(A_1) dF(A_2).
\]

The consumer welfare for each firm can be expressed as follows:

\[
CW_1^A = \int_{A_2} \int_{A_1} \frac{1}{2} \left( \frac{A_1 - k_1 A_2 + b_1 p_1^A}{a_1} - p_1^A \right) q_1^A dF(A_1) dF(A_2)
\]

\[
= \int_{A_2} \int_{A_1} \frac{1}{2} \left( \frac{q_1^A + a_1 p_1^A}{a_1} - p_1^A \right) q_1^A dF(A_1) dF(A_2) = \frac{1}{2a_1} \int_{A_2} \int_{A_1} (q_1^A)^2 dF(A_1) dF(A_2),
\]

\[
CW_2^A = \frac{1}{2a_2} \int_{A_2} \int_{A_1} (q_2^A)^2 dF(A_1) dF(A_2).
\]

The overall consumer welfare is defined as the sum of the consumer surplus of Firm 1 and Firm 2: $CW^A := CW_1^A + CW_2^A$. 

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A.2 Perfect Information

In the perfect information scenario, both firms have knowledge of $A_1$ and $A_2$, and prices can be expressed as follows:

$$p_1^P = \frac{2A_1a_2 - A_1k_2(b_1 + rb_2) + A_2(b_1 - 2a_2k_1 + rb_2)}{4a_1a_2 - b_2(b_1 + rb_2)} = p_1^A + \frac{(\eta A_1 - A_1)k_2(b_1 + rb_2)}{4a_1a_2 - b_2(b_1 + rb_2)}$$

$$p_2^P = \frac{2A_2 - A_1b_2 + 2a_2A_1k_2}{-4a_1a_2 + b_2(b_1 + rb_2)} = p_2^A + \frac{2a_1(\eta A_1 - A_1)k_2}{4a_1a_2 - b_2(b_1 + rb_2)} := p_2^A + \Delta p_2^{A,P}.$$ 

Increased price competition

Improved pricing response to competitors' information

Compared to the information advantage scenario, Firm 2 will now undercut competitors when in a higher demand state (higher $A_1$) and raise prices when in a lower demand state (lower $A_1$). This change in Firm 2's strategy will result in increased price competition for Firm 1.

Quantities are given by the following and have a simple relationship with the prices:

$$q_1^P = q_1^A + \frac{a_1A_1A_1 - A_1)k_2(b_1 - rb_2)}{4a_1a_2 - b_2(b_1 + rb_2)} := q_1^A + \Delta q_1^{A,P},$$

$$q_2^P = q_2^A + \frac{(A_1 - \eta A_1)k_2(2a_1a_2 - b_2(b_1 + rb_2))}{4a_1a_2 - b_2(b_1 + rb_2)} := q_2^A + \Delta q_2^{A,P}.$$ 

Expected Profits The expected profit for Firm 1 can be written as follows:

$$\mathbb{E}[\Pi_1^P] = \int_{A_2} \int_{A_1} (p_1^A + \Delta p_1^{A,P})(q_1^A + \Delta q_1^{A,P})dF(A_1)dF(A_2)$$

$$= \mathbb{E}[\Pi_1^A] + \int_{A_1} \int_{A_2} \left( p_1^A \Delta q_1^{A,P} + \Delta p_1^{A,P} \Delta q_2^{A,P} \right) dF(A_2)dF(A_1)$$

$$= \mathbb{E}[\Pi_1^A] + \int_{A_1} \left( (A_1 - \eta A_1)A_1dF(A_1) \right).$$

When there are no vertical incentives ($r = 0$), Firm 1’s profit decreases after losing its information advantage over Firm 2, as shown in Figure A.1a. However, when
vertical incentives exist \((0 < r < 1)\), the outcome depends on two factors: the loss of direct sales due to the absence of the information advantage and the potential gain from referral fee revenue. If the potential gain outweighs the loss, Firm 1 may end up better off. The revenue-neutral \(k_2\) is the value at which \(\Pi_1^P = \Pi_1^A\), and the shaded region between the profit and revenue-neutral lines in Figure A.1a represents the profit change for other \(k_2\) values. The expected profit for Firm 2 can be written as follows:

\[
E[\Pi_2^P] = E[\Pi_2^A] + \int_{A_1} \int_{A_2} \left( p_2^A \Delta q_2^{A,P} + \Delta p_2^{A,P} a_2 p_2^P \right) dF(A_2) dF(A_1) \\
= \int_{A_1} \left[ \frac{\text{Gain from better pricing}}{4a_1^2 a_2 k_2} - \frac{\text{Loss from intensified competition}}{b_2^2 (b_1 + rb_2)} \right] \left( \int_{A_1} (A_1 - \eta A_1) A_1 dF(A_1) \right) \\
> E[\Pi_2^A] \iff k_2 > \frac{b_2^2(b_1 + rb_2)}{4a_1^2 a_2}.
\]

Perfect information generally benefits Firm 2, particularly when \(k_2\) values are large. However, compared to the information advantage case, its profit can still decrease. Figure A.1b illustrates a numerical example where the revenue-neutral \(k_2\) is \(\frac{b_2^2(b_1 + rb_2)}{4a_1^2 a_2}\), and \(\Pi_2^P = \Pi_2^A\) at this point. When \(k_2\) is low, Firm 2’s profit increases if \(A_1\) is greater than the average and decreases if \(A_1\) is less than the average. However, the loss outweighs the gain, leading to lower profits for Firm 2.

The intuition is as follows: When Firm 2 knows \(A_1\), it charges a lower price when \(A_1\) is high and a higher price when \(A_1\) is low, intensifying price competition when \(A_1\) is high and softening it when \(A_1\) is low. If the increased competition outweighs the benefit of the imperfect information, it can result in a decline in Firm 2’s profit.
Figure A.1: Effect of Variable $k_2$ on Profits

Note: Figure A.1 displays a simulation with parameters $a_1 = 12.1, a_2 = 2.3, b_1 = 10, b_2 = 1.3, k_1 = 0.2, A_2 = 10$, and $E[A_1] = 10$, and $r = 15\%$. The concept of a “budget neutral” $k$ refers to the value that equalizes the firm’s profit to that of the information advantage case.

Consumer Welfare The consumer welfare for Firm 1 can be written as

$$CW_1^P = \frac{1}{2a_1} \int_{A_2} \int_{A_1} (q_1^P)^2 dF(A_1)dF(A_2) = \frac{1}{2a_1} \int_{A_2} \int_{A_1} (q_1^A + \Delta q_1^{A,P})^2 dF(A_1)dF(A_2)$$

$$= CW_1^A + \frac{1}{2a_1} \int_{A_2} \int_{A_1} (q_1^A + q_1^P) \Delta q_1^{A,P} dF(A_2)dF(A_1)$$

$$= CW_1^A + \frac{k_2(b_1 - rb_2)(2rb_2^2 - 4a_1a_2 + a_1k_2(b_1 - rb_2))}{2(4a_1a_2 - (b_1 + rb_2)b_2)^2} \int_{A_1} (A_1 - \eta A_1) A_1 dF(A_1) \leq CW_1^A.$$
Firm 2:

\[ CW_2^P = CW_2^A + \frac{1}{2a_2} \int_{A_2} \int_{A_1} (q_2^A + q_2^P) \Delta q_2^{A,P} dF(A_1)dF(A_2) \]

\[ = CW_2^A + k_2(2a_1a_2 - b_2(b_1 + rb_2))(2a_2(b_2 - 3a_1k_2) + b_2k_2(b_1 + rb_2)) \]

\[ \int_{A_1} (A_1 - \eta A_1)A_1 dF(A_1). \]

The welfare of Firm 2’s consumers decreases as long as \( k_2 \) is sufficiently large, aligning with the fact that a larger \( k_2 \) results in decreased profits for Firm 2. The overall consumer welfare decreases when \( k_2 \) is sufficiently large.

\[ CW^P \geq CW^A \iff k_2 < \frac{2a_2(2a_1a_2(b_1 - b_2(1 + r)) + b_2^2(b_1 - b_1r + b_2r(1 + r)))}{a_1a_2(b_2^2 + rb_2(8b_2 + rb_2) + b_1(b_2(-8 + r) + rb_2)) - 12a_1^2a_2^2 - b_2^2(b_1 + rb_2)^2}. \]

As shown in Figure A.2a, consumers benefit when \( A_1 \) is high because competition is intensified, but they suffer more when \( A_1 \) is low because competition is softened. However, consumer welfare can actually increase under perfect information compared to the information advantage scenario. When \( k_2 \) is small and Firm 2’s cross-elasticity of demand \( b_2 \) is much larger than Firm 1’s \( b_1 \), it becomes more likely that the gains from intensified competition when \( A_1 \) is high for Firm 2’s consumers slightly outweigh the losses from softened competition when \( A_1 \) is low.

### A.3 Limited Information

In the limited information scenario, each firm has knowledge only of their own \( A \), with Firm 1 observing only \( A_1 \) and Firm 2 observing only \( A_2 \). The prices under this situation can be represented as follows:

\[ p_1^L = \frac{2A_1a_2 - 2a_2\eta A_2k_1 + (A_2 - \eta A_1k_2)(b_1 + rb_2)}{4a_1a_2 - b_2(b_1 + rb_2)} = p_1^A + \frac{2a_2(A_2 - \eta A_2)k_1}{4a_1a_2 - b_2(b_1 + rb_2)} \]

\[ \text{Inferior pricing without competitor information} \]

\[ : = p_1^A + \Delta p_1^{A,L}, \]

\[ p_2^L = \frac{2a_1A_2 + A_1b_2 - b_2\eta A_2k_1 - 2a_1\eta A_1k_2}{4a_1a_2 - b_2(b_1 + rb_2)} = p_2^A + \frac{b_2(A_2 - \eta A_2)k_1}{4a_1a_2 - b_2(b_1 + rb_2)} \]

\[ \text{Softened price competition} \]

\[ : = p_2^A + \Delta p_2^{A,L}. \]
Figure A.2: Effect of Variables $k_1$ and $k_2$ on Consumer Welfare

Note: Figure A.2 displays a simulation with parameters $a_1 = a_2 = 8, E[A_1] = E[A_2] = 10$, and $r = 15\%$. Additionally, Figure A.2a has $b_1 = 1, b_2 = 5, k_1 = 0.2$, and $A_2 = 10$, while Figure A.2b has $b_1 = 5, b_2 = 1, k_2 = 0.05$, and $A_1 = 10$. The concept of a “welfare neutral” $k$ refers to the value that equalizes the overall consumer welfare to that of the information advantage case.

Firm 1 no longer undercut Firm 2 when its demand state is high (High $A_2$) but lowers prices when Firm 2 has a low demand state (Low $A_2$). This change reduces price competition, which has a direct impact on Firm 2.

The quantity meets the following conditions:

\[
q_1^L = q_1^A + \frac{(2a_1a_2 - b_1b_2)(\eta_{A_2} - A_2)k_1}{4a_1a_2 - b_2(b_1 + rb_2)} := q_1^A + \Delta q_1^{A,L},
\]

\[
q_2^L = q_2^A + \frac{a_2b_2(A_2 - \eta_{A_2})k_1}{4a_1a_2 - b_2(b_1 + rb_2)} := q_2^A + \Delta q_2^{A,L}.
\]
**Expected Profits**  Firm 1’s expected profit in the scenario of limited information is as follows

\[
E[\Pi_1^L] = E[\Pi_1^A] + \int_{A_2} \int_{A_1} (p_1^A \Delta q_2^{A,L} + \Delta p_1^{A,L} q_2^L) dF(A_1) dF(A_2)
\]

\[
= E[\Pi_1^A] + \frac{k_1}{(4a_1a_2 - b_2(b_1 + rb_2))^2} \left( \int_{A_2} (A_2 - \eta_{A_2}) A_2 dF(A_2) \right).
\]

For most large \(k_1\) values, Firm 1 is generally worse off than in the information advantage case. However, there are scenarios where Firm 1 could still benefit. In the simulation shown in Figure A.3, the revenue-neutral \(k_1\) is \(\frac{b_2 - 4a_1a_2rb_2 + b_1b_2rb_2}{4a_1a_2^2 - 2a_2b_2rb_2}\), resulting in \(\Pi_1^L = \Pi_1^A\). When \(k_1\) is high, Firm 1’s profit decreases when \(A_2\) is less than the average and increases when \(A_2\) is larger than the average. However, the gain dominates the loss, leading to higher profits for Firm 1.

Since Firm 1 does not know \(A_2\), it charges higher prices when \(A_2\) is high and lower prices when \(A_2\) is low, compared to the information advantage case. This intensifies competition when \(A_2\) is low and softens competition when \(A_2\) is high. When the benefit of reduced competition outweighs the cost of imperfect information, Firm 1 may benefit.

In addition, Firm 2’s expected profit under the limited information scenario can be expressed as:

\[
E[\Pi_2^L] = E[\Pi_2^A] + \int_{A_2} \int_{A_1} (p_2^A \Delta q_2^{A,L} + \Delta p_2^{A,L} q_2^L) dF(A_1) dF(A_2)
\]

\[
= E[\Pi_2^A] + \frac{k_1a_2b_2(4a_1 - k_1b_2)}{(4a_1a_2 - b_2(b_1 + rb_2))^2} \left( \int_{A_2} (A_2 - \eta_{A_2}) A_2 dF(A_2) \right) \geq E[\Pi_2^A].
\]

Firm 2’s profits increase in comparison to the scenario where Firm 1 has an information advantage.
Figure A.3: Effect of Variable $k_1$ on $\Pi_1^L - \Pi_1^A$

Note: Figure A.3 displays a simulation with parameters $a_1 = 12, a_2 = 10, b_1, 10, b_2 = 5, k_1 = 0.2$, and $r = 15\%$. Additionally, Figure A.1b has $A_1 = 10$, and $E[A_2] = 10$, while Figure A.3 has $A_2 = 10$, and $E[A_1] = 10$. The concept of a “budget neutral” $k$ refers to the value that equalizes the firm’s profit to that of the information advantage case.

Consumer Welfare The consumer welfare for Firm 1 can be written as

$$CW_1^L = CW_1^A + \frac{1}{a_1} \int_{A_2} \int_{A_1} (q_1^A + q_1^L) \Delta q_1^{A,L} dF(A_1) dF(A_2)$$

$$= CW_1^A + \frac{k_1(2a_1a_2 - b_1b_2)(2a_1(-b_1 + 3a_2k_1 + rb_2) - b_2k_1(b_1 + 2rb_2))}{2a_1(4a_1a_2 - (b_1 + rb_2)b_2)^2}$$

$$\int_{A_2}(A_2 - \eta_{A_2})A_2 dF(A_2) \geq CW_1^A \iff k_1 > \frac{2(a_1b_1 - a_1rb_2)}{6a_1a_2 - b_1b_2 - 2b_2rb_2}.$$
Firm 1’s consumer welfare increases with sufficiently large \( k_1 \), consistent with Firm 1’s decreasing profit. On the other hand, the consumer welfare for Firm 2 is as follows:

\[
CW_2^L = CW_2^A + \frac{1}{a_2} \int_{A_2} \int_{A_1} (q_2^A + q_2^L) \Delta q_2^{A,L} dF(A_1) dF(A_2)
\]

\[
= CW_2^A + \frac{a_2 b_2 k_1 (4a_1 - b_2 k_1)}{2(4a_1 a_2 - (b_1 + rb_2) b_2)^2} \int_{A_2} (A_2 - \eta_{A_2}) A_2 dF(A_2) \geq CW_2^A.
\]

The welfare of Firm 2’s consumers increases as Firm 1 is unable to factor in information from \( A_2 \) when setting their prices. An increase in overall consumer welfare compared to the information advantage case is indicated when the following inequality is satisfied:

\[
CW_2^L > CW_2^A \iff k_1 > \frac{2a_2 (2a_1 a_2 (b_1 - b_2 - rb_2) + b_1 b_2 (b_2 - rb_2) + b_2 r b_2 (b_2 + rb_2))}{12a_1^2 a_2^2 + b_2^2 (b_1 + rb_2)^2 - a_1 a_2 (b_1^2 + 8b_1 b_2 - 2b_1 r b_2 + 8b_2 r b_2 + r b_2^2)}
\]

As depicted in Figure A.2b, when \( k_1 \) is sufficiently large, the overall consumer welfare generally increases. The intensified competition in Firm 2’s market when \( A_2 \) is low leads to welfare gains, while the softened competition in the same market when \( A_2 \) is high results in welfare losses. However, under limited information relative to the information advantage case, it is still possible for consumer welfare to decrease. This occurs primarily when \( k_1 \) is small and Firm 1’s cross-elasticity of demand \( b_1 \) is much larger than that of Firm 2’s \( b_2 \). In such a scenario, the intensified competition when \( A_2 \) is low benefits Firm 1’s consumers, but the softened competition when \( A_2 \) is high leads to losses that slightly outweigh the gains.

**B Disclosure of Sales Information**

The disclosure of data is a major design decision actively made by platforms. As for the disclosure of sales data, there is no consensus in the industry. Table A.1 presents a listing of 19 e-commerce websites. This listing is accompanied by the respective primary operational regions of these websites, along with an indicator whether these platforms disclose sales data or not.

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Figure A.4a illustrates an example of sales data disclosure on an e-commerce platform. Other platforms that make sales data open typically follow a similar format. Figure A.4b, sourced from Waters (2023), is an example of Amazon’s public disclosure of sales data. The incidents started around March 2023, and as of October 2023, it still appears to be selective and random. Moreover, due to differences in platform design, Amazon’s disclosure is at the product level instead of the seller-listing level, given the presence of multiple competing listings for a single product on Amazon. Nevertheless, if implemented on a larger scale, this could be seen as a significant step in Amazon’s sharing of sales information.³⁸

Figure A.4: Public Sales Data on e-Commerce Platform: Examples

(a) eBay  
(b) Amazon (Recent Experimentation)

Note: Figure A.4a displays open sales data on eBay, while Figure A.4b displays open sales data on Amazon, which is currently in the experimental phase.

³⁸Amazon offers a program called Amazon Brand Analytics, which aims to provide “the right data” to brand owners (see https://sell.amazon.com/blog/brand-analytics). This seems to fit in a plausible trend of Amazon sharing more data with third-party sellers.
Table A.1: Disclosure of Sales Data by E-commerce Websites

<table>
<thead>
<tr>
<th>Website</th>
<th>Region</th>
<th>Disclose Sales Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>AliExpress</td>
<td>International</td>
<td>Yes</td>
</tr>
<tr>
<td>eBay</td>
<td>US</td>
<td>Yes</td>
</tr>
<tr>
<td>Walmart</td>
<td>US</td>
<td>No</td>
</tr>
<tr>
<td>Best Buy</td>
<td>US</td>
<td>No</td>
</tr>
<tr>
<td>Target</td>
<td>US</td>
<td>No</td>
</tr>
<tr>
<td>Zalando</td>
<td>Europe</td>
<td>No</td>
</tr>
<tr>
<td>Allegro</td>
<td>Europe</td>
<td>Yes</td>
</tr>
<tr>
<td>Cdiscount</td>
<td>Europe</td>
<td>No</td>
</tr>
<tr>
<td>Yahoo! Japan Shopping</td>
<td>Japan</td>
<td>No</td>
</tr>
<tr>
<td>ZOZOTOWN</td>
<td>Japan</td>
<td>No</td>
</tr>
<tr>
<td>Mercari</td>
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<td>Yes</td>
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<td>Lazada</td>
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<td>Zalora</td>
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<td>No</td>
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<tr>
<td>Qoo10</td>
<td>Southeast Asia</td>
<td>Yes</td>
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<td>Yes</td>
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<td>JD.com</td>
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<td>Pinduoduo</td>
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<td>Yes</td>
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<tr>
<td>Suning</td>
<td>China</td>
<td>No</td>
</tr>
</tbody>
</table>

Note: Table A.1 lists the 19 e-commerce websites, their primary operating regions, and whether these websites disclose sales measures or not.

C Price Variation

Prices on the Amazon marketplace are known for their frequent fluctuations. We investigate the frequency and magnitude of price adjustments, which are defined as changes in price from one day to the next. As presented in Table A.2, third-party sellers have a 2.79% likelihood of adjusting their prices, while Amazon has a 5.68% likelihood of adjusting prices. Prices can be adjusted upwards or downwards, and
for both third-party sellers and Amazon, prices are more likely to decrease than increase. On average, a price adjustment results in a \(-0.39\) change for third-party sellers and a \(-0.37\) change for Amazon. When prices are decreased, the average price decrease is $4.43 for third-party sellers and $4.63 for Amazon. When prices are increased, the average price increase is $5.26 for third-party sellers and $5.53 for Amazon. Compared to third-party sellers, Amazon is more likely to adjust its prices and make larger changes.

Table A.2: Price Variation

<table>
<thead>
<tr>
<th></th>
<th>Third-Party Sellers</th>
<th>Amazon</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>STD</td>
</tr>
<tr>
<td>Price Adjustment Probability (%)</td>
<td>2.79</td>
<td>16.47</td>
</tr>
<tr>
<td>Price Decrease Probability (%)</td>
<td>1.63</td>
<td>12.66</td>
</tr>
<tr>
<td>Price Increase Probability (%)</td>
<td>1.16</td>
<td>10.72</td>
</tr>
<tr>
<td>Price Change ($)</td>
<td>-0.39</td>
<td>21.16</td>
</tr>
<tr>
<td>Price Decrease Change ($)</td>
<td>-4.43</td>
<td>23.30</td>
</tr>
<tr>
<td>Price Increase Change ($)</td>
<td>5.26</td>
<td>16.11</td>
</tr>
</tbody>
</table>

Note: Table A.2 shows the probability of a price adjustment and the magnitude of the corresponding price change for third-party sellers and Amazon, respectively.

D Sales Error Probability from Restocking

One concern for inaccuracies in our sales measures is the restocking of products. We track the stock levels of approximately 2,400 products on an bi-hourly basis. Using the high frequency data, we can more effectively differentiate between sales occurrences and product restocking. We identify these restocking events and compare how likely it is to underestimate sales in scenarios where the stock data is on a daily or weekly basis.
In Table A.3, we calculate the probability of underestimating sales as a result of restocking events. When the data is at a daily level, the likelihood of having measurement errors due to restocking is less than 1%. As expected, this probability increases as the data frequency becomes less frequent, such as when using weekly data, where there is a 7.12% chance of having measurement errors attributable to restocking.

<table>
<thead>
<tr>
<th>Stock Data Frequency</th>
<th>Probability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Day</td>
<td>0.98</td>
</tr>
<tr>
<td>2 Days</td>
<td>2.15</td>
</tr>
<tr>
<td>3 Days</td>
<td>3.12</td>
</tr>
<tr>
<td>4 Days</td>
<td>4.14</td>
</tr>
<tr>
<td>5 Days</td>
<td>5.22</td>
</tr>
<tr>
<td>6 Days</td>
<td>6.06</td>
</tr>
<tr>
<td>7 Days</td>
<td>7.12</td>
</tr>
</tbody>
</table>

Note: Table A.3 presents probabilities of sales underestimation due to restocking events at different stock data frequency levels.

E Automated Pricing Services

Amazon provides professional sellers with a free automated pricing tool that adjusts prices in “real time” based on either competitor prices (namely the “Featured Offer Rule” and “Competitive Price Match Rule”) or their own sales, known as the “Sales Bases Rule.” ³⁹ The former allows sellers to monitor and react to competition, while the latter explicitly incorporates a pricing strategy that is contingent on own sales.

³⁹See https://sell.amazon.com/tools/automate-pricing.
but not on competitors’ sales.

Furthermore, we conduct a survey of leading providers of automated pricing services in the market. For each of these providers, we summarize the data used in their technology in Columns 2 and 3 of Table A.4. Apart from considering competitors’ prices, most automated pricing service providers offer adjustments based on sellers’ own sales, often referred to as “Sales Velocity Repricing.” However, none of the companies claim to possess the capability to set prices based on competitors’ sales.

Column 4 of Table A.4 presents our survey results regarding the repricing frequency offered by each provider. With the exception of one provider primarily offering A/B testing services, the rest claim to reprice instantaneously. In practice, this means repricing is typically completed within seconds, 2 to 3 minutes, or as fast as Amazon allows.

F Response Patterns of Large and Small Sellers

We examine whether the responses to one’s own sales events and a competitor’s sales events may depend on whether a third-party seller is large or small. A large seller might be more sophisticated or equipped with better technology. So, if our reduced-form evidence is driven by seller sophistication or technology, rather than information, we would expect to observe that large sellers respond more similarly to Amazon and differ from small sellers.

We define large sellers as those with the top 10% number of seller ratings, meaning a number of seller rating greater than approximately 17,500. Amazon aggregates seller ratings for different products at the seller level, so a greater number of seller rating is associated with sellers who have more aggregate sales and are larger in size.

Figure A.5 displays the responses to a sales event for both large and small third-

\[40\text{See https://www.marketplacepulse.com/landscape.}\]
Table A.4: Automated Pricing Services

<table>
<thead>
<tr>
<th>Company</th>
<th>Competitor’s Price</th>
<th>Own Sales</th>
<th>Instant Repricing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Aura</td>
<td>✓</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td>Bqtools</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Channelmax</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Eva</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Feedvisor360</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Flashpricer</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Informed</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Priceloop</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Repricer.com</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Seller Snap</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Note: Table A.4 summarizes each of the leading providers of automated pricing services, the data they claim to use in their pricing technology in Columns 2 and 3, and whether they claim to have instant repricing in Column 4.

party sellers. Similar to the patterns observed between Amazon and third-party sellers, large third-party sellers also exhibit faster and larger responses in the price levels compared to small third-party sellers. However, in Figure A.6, both large and small third-party sellers are unresponsive to the competitor’s sales event. Therefore, the heterogeneity in response to competitor’s sales events between Amazon and third-party sellers are better explained by asymmetric information.
Figure A.5: Response of Large and Small Third-Party Sellers to a Sales Event

(a) Large Third-Party Sellers  
(b) Small Third-Party Sellers

Note: Figure A.5 displays the estimates from Equation 2 using the price level as the dependent variable for large and small third-party sellers, respectively, before and after a sales event. The vertical line indicates the day of a sales event. We define large sellers as those with the top 10% number of seller ratings. The robust standard errors are clustered at the product level.
Figure A.6: Response of Large and Small Third-Party Sellers to Competitor’s Sales Event

(a) Large Third-Party Sellers

(b) Small Third-Party Sellers

Note: Figure A.6 displays the estimates from Equation 2 using the price level as the dependent variable for large and small third-party sellers, respectively, before and after a competitor’s sales event. The vertical line indicates the day of a competitor’s sales event. We define large sellers as those with the top 10% number of seller ratings. The robust standard errors are clustered at the product level.
G  Price Adjustments

We consider two types of outcomes related to pricing. First, we differentiate the
direction of price adjustments and define the cumulative number of price adjustments
in each direction for each event $s$ on its event day $\tilde{t}$. For instance, to count price
increases for an event $s$, we sum up the instances when the price on a particular day,
$p_{s,\tilde{t}}$, is greater than the previous day’s price, $p_{s,\tilde{t}-1}$. More formally, for all $s \in S^\text{no sales}$,
we define the cumulative number of price increases $\zeta_{s,\tilde{t}}^\uparrow$ and decreases $\zeta_{s,\tilde{t}}^\downarrow$
as
\begin{align*}
\zeta_{s,\tilde{t}}^\uparrow &= \begin{cases} 
\sum_{\tau=2}^{\tilde{t}} \mathbb{1}(p_{s,\tau-1} < p_{s,\tau}) & \text{if } \tilde{t} \in \{2, \ldots, 7\}, \\
0 & \text{if } \tilde{t} = 1;
\end{cases} \\
\zeta_{s,\tilde{t}}^\downarrow &= \begin{cases} 
\sum_{\tau=2}^{\tilde{t}} \mathbb{1}(p_{s,\tau-1} > p_{s,\tau}) & \text{if } \tilde{t} \in \{2, \ldots, 7\}, \\
0 & \text{if } \tilde{t} = 1.
\end{cases}
\end{align*}

(A.1)

G.1 No-Sales Events

In Figure A.7, we present the estimates of $\gamma_{\tau}$ obtained from Equation A.1 using the
cumulative number of price increases $\zeta_{s,\tilde{t}}^\uparrow$ and decreases $\zeta_{s,\tilde{t}}^\downarrow$ as dependent variables
for third-party sellers and Amazon, respectively. The findings suggest that, during
consecutive days of no sales, prices tend to decrease more often than they increase.
This pattern is consistent for both Amazon and third-party sellers.

G.2 Sales Events

We examine the frequency and direction of price adjustments using the cumulative
number of price increases $\zeta_{s,\tilde{t}}^\uparrow$ and decreases $\zeta_{s,\tilde{t}}^\downarrow$ for Amazon and third-party sellers,
respectively. We define these variables similarly to Section 4.1, but restrict $s$ to be in
the set $S^\text{sales}_3$ and $\tilde{t}$ to take values from -4 to 3. As shown in Figure A.8, both third-party sellers and Amazon are more likely to increase their prices following a sales
Figure A.7: Cumulative Number of Price Adjustments during Consecutive Days of No Sales

(a) Price Increase: Amazon  
(b) Price Increase: Third-Party Sellers  
(c) Price Decrease: Amazon  
(d) Price Decrease: Third-Party Sellers

Note: Figure A.7 shows the estimates from Equation 1 during consecutive days of no sales using the cumulative number of price adjustments as the dependent variables for third-party sellers and Amazon, respectively. Figure A.7a and Figure A.7b present the cumulative number of price increases and Figure A.7c and Figure A.7d present the cumulative number of price decreases. The robust standard errors are clustered at the product level.

Additionally, sellers are less likely to lower their prices after a sales event.41

41The outcomes in Figure A.9c and Figure A.9d are the cumulative number of price decreases, which is expected to increase over time only. However, we control for a linear trend, so the estimate can decrease if the increase in the cumulative number is less than the linear trend.
Figure A.8: Price Adjustments After a Sales Event

(a) Price Increase: Amazon

(b) Price Increase: Third-Party Sellers

(c) Price Decrease: Amazon

(d) Price Decrease: Third-Party Sellers

Note: Figure A.8 shows the estimates from Equation 2 using the cumulative number of price adjustments as the dependent variable for third-party sellers and Amazon, respectively, before and after sales events. Figure A.8a and Figure A.8b present the cumulative number of price increases and Figure A.8c and Figure A.8d present the cumulative number of price decreases. The vertical line indicates the day of the sales event. The robust standard errors are clustered at the product level.

G.3 Sellers prices depending on their past sales

We investigate the relationship between a seller’s current price and their past sales by measuring the number of days in which the seller has made any sales in the past.
Specifically, we define the number of days with sales in the past as the following:

\[
R_{\text{sales}}^{m,j,t} = \sum_{r=1}^{\tau} I(q_{m,j,t-r} > 0).
\]

We choose \(\tau = 7\), meaning that \(R_{\text{sales}}^{m,j,t}\) captures the number of days with sales in the past week. We then use the following specification to understand how the current price may vary based on the number of days with sales in the past week:

\[
y_{m,j,t} = \sum_{\tau=0}^{4} \gamma \times I(R_{\text{sales}}^{m,j,t} = \tau) + \theta_{m,j} + \lambda_{t} + \iota_{m,j,t} + \epsilon_{m,j,t}.
\]

(A.2)

In Equation A.2, the variable \(y_{m,j,t}\) represents the outcome of seller \(j\) in market \(m\) on day \(t\). The indicator variable \(I(R_{\text{sales}}^{m,j,t} = \tau)\) takes a value of 1 if the observation has \(\tau\) days of sales in the past week. The term \(\theta_{m,j}\) represents seller-market fixed effects, which allow us to compare prices of the same seller in a given market based on the number of days during the past week when the seller made any sales. The term \(\lambda_{t}\) represents daily fixed effects, which capture the variation in prices across calendar dates. We also control for inventory fixed effects \((\iota_{m,j,t})\) in order to isolate the effects of inventory on prices.

We present the estimates of \(\gamma\) from Equation A.2, using the cumulative number of price increases \(\zeta_{m,j,t}^{+}\) and decreases \(\zeta_{m,j,t}^{-}\), as defined in Equation A.1, in Figure A.9. Both third-party sellers and Amazon tend to increase their prices more and decrease their prices less frequently when they have had more days with sales in the past week.

Furthermore, we present the estimates of \(\gamma_{\tau}\) in Figure A.10, using the price \(p_{m,j,t}\) as the dependent variable in Equation A.2. The average price increase is larger when a seller has had more days with sales in the past, consistent with our findings for the probability of price adjustments.

G.3.1 Correlated Demand

The estimates of \(\gamma_{\tau}\) using sales \(q_{m,j,t}\) as the dependent variable are displayed in Figure A.11, indicating a positive correlation between past sales and current sales. This
Figure A.9: Price Adjustments Over Number of Days With Sales During The Past Week

Note: Figure A.9 plots the estimates from Equation A.2 over the number of days with sales during the past week using the probability of a price adjustment as the dependent variable for third-party sellers and Amazon, respectively. Figure A.9a and Figure A.9b present the probability of a price increase, and Figure A.9c and Figure A.9d present the probability of a price decrease. The robust standard errors are clustered at the product level.

implies that sales are autocorrelated and that a higher number of past sales is associated with a greater likelihood of higher sales in the present.
Figure A.10: Price Levels Over Number of Days With Sales During The Past Week

Note: Figure A.10 plots the estimates from Equation A.2 over the number of days with sales during the past week using the price level as the dependent variable for third-party sellers and Amazon, respectively. The robust standard errors are clustered at the product level.

Figure A.11: Sales Over Number of Days With Sales During The Past Week

Note: Figure A.11 plots the estimates from Equation A.2 over the number of days with sales during the past week using the log of sales as the dependent variable for third-party sellers and Amazon, respectively. The robust standard errors are clustered at the product level.
G.4 Competitor’s Sales Events

In Figure A.12, we plot the estimates of $\gamma_r$ using the cumulative number of price adjustments as the dependent variable for Amazon and third-party sellers, respectively. According to our findings in Section 4.2, after a competitor’s sales event, the competitor increases its price. In equilibrium, Amazon and third-party sellers may also increase their prices in response. We introduce a structural model of price competition that deals with this equilibrium effect in Section 5.

Interestingly, we find that Amazon may reduce its prices following a competitor’s sales event. The frequency of price decreases for Amazon is approximately ten times greater than that of third-party sellers. This effect is highly significant for Amazon, while it is insignificant for third-party sellers when the pretrend is taken into account.
Figure A.12: Price Adjustments After a Competitor’s Sales Event

(a) Price Increase: Amazon

(b) Price Increase: Third-Party Sellers

(c) Price Decrease: Amazon

(d) Price Decrease: Third-Party Sellers

Note: Figure A.12 displays the estimates from Equation 2 using the cumulative number of price adjustments as the dependent variable for third-party sellers and Amazon, respectively, before and after a competitor’s sales events. Figure A.12a and Figure A.12b present the cumulative number of price increases and Figure A.12c and Figure A.12d present the cumulative number of price decreases. The vertical line indicates the day of a competitor’s sales event. The robust standard errors are clustered at the product level.
H Estimation of Demand States

To address the potential bias in the coefficient of $\eta$ caused by the endogeneity of prices when estimating Equation 8, we use the log of inventory as an instrument for price. The inventory level serves as a cost shifter since sellers may face higher costs when they have excess inventory due to storage costs.

In Column 1 of Table A.5, we present the results of the first-stage regression, which indicate that prices tend to increase with higher log inventory levels. In Column 2 of Table A.5, we provide the estimates from the IV regression. As expected, the coefficient of the price is negative.

<table>
<thead>
<tr>
<th>Table A.5: Estimation of Demand States</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) First Stage</td>
</tr>
<tr>
<td>log($I_{m,j,t}$)</td>
</tr>
<tr>
<td>$p_{m,j,t}$</td>
</tr>
<tr>
<td>Product-Seller Fixed Effects</td>
</tr>
<tr>
<td>No. of Observations</td>
</tr>
</tbody>
</table>

Note: Table A.5 shows the results from Equation 8. The first stage estimates are presented in Column 1 and the two-stage least squares (2SLS) estimates are displayed in Column 2. The robust standard errors are cluster at the product level. The significance levels are indicated as follows: *(p < 0.10), **(p < 0.05), ****(p < 0.01).

I Moment Conditions

The vector $z_{m,j,i} = M_{m,j,i} \otimes H_{m,j,i} \otimes T_{m,j,i}$ represents a vector of 160 indicators, where $M$ represents the 5 market structures ($5 \times 1$), $H$ represents the combinations of best
predicted and true demand states of focal seller and the competitor (16 × 1), and \( T \) represents the period before and after repricing (2 × 1) as the following:

\[
M_{m,j,t} = \begin{bmatrix}
1(\mathcal{M}(m) = \text{AMZ-vs-FBM}) \\
1(\mathcal{M}(m) = \text{AMZ-vs-FBA}) \\
1(\mathcal{M}(m) = \text{FBA-vs-FBM}) \\
1(\mathcal{M}(m) = \text{FBA-vs-FBA}) \\
1(\mathcal{M}(m) = \text{FBMvs-FBM})
\end{bmatrix},
\]

\[
H_{m,j,t} = \begin{bmatrix}
1(\hat{h}_{m,j,t} = 1) \\
1(\hat{h}_{m,j,t} = 0) \\
1(\hat{h}_{m,-j,t} = 1) \\
1(\hat{h}_{m,-j,t} = 0)
\end{bmatrix} \otimes \begin{bmatrix}
1(l_{BP}^{BP} = 1) \\
1(l_{BP}^{BP} = 0) \\
1(l_{BP}^{BP} = 1) \\
1(l_{BP}^{BP} = 0)
\end{bmatrix}, \text{ and } T_{m,j,t} = \begin{bmatrix}
1(\tilde{t} = 1) \\
1(\tilde{t} = -1)
\end{bmatrix}.
\]

### J Welfare Calculation

For each scenario, we calculate sellers’ profits based on Equation 7. We compute consumer welfare using the following equation:

\[
CW = \sum_{m,t} \lambda_{m,t} \times \frac{\log (\exp (\rho \times \log (D_{m,t})) + 1)}{\alpha}.
\]

Social welfare is the sum of surplus and profits across consumers, sellers, and Amazon. In markets where Amazon is not present as a seller, we include its revenue from referral fees in the calculation of social welfare. The formula is as follows:

\[
SW = CW + \sum_{m,t} \sum_{j \in J_{m,t}} \Pi_{m,j,t} + \left(1 - \max_{j \in J_{m,t}} a(j)\right) \times r_m \times p_{m,j,t}.
\]

Referral fee in third-party-only markets

### K Information Sharing in Third-Party-Only Markets

Information sharing among third-party sellers can significantly impact markets where these sellers compete with one another, and Amazon does not operate as a seller.
Given no prior information advantage among third-party sellers, we essentially compare two scenarios where competitors have equal information access, but the volume of market information varies.

The counterfactual outcomes for this scenario are delineated in Table A.6. In markets characterized by the presence of one FBA seller and one FBM seller, consumer welfare and social welfare experience a decrease of 1.22% as competition weakens and both sellers elevate their prices. Concurrently, the total profit for sellers witnesses a 2.21% increase. Amazon’s referral fee earnings decrease as a result of the overall decrease in transactions. This decrease in competition could be due to the asymmetry among sellers.

When competitors’ sales information is available, FBA-vs-FBA and FBM-vs-FBM markets become more competitive, leading to average price reductions of 3.34% and 0.85%, respectively. Consequently, a larger share of welfare is allocated to consumers, resulting in a significant increase in consumer welfare by 35.84% and 2.5%, respectively. In addition, social welfare increases by 18.82% and 0.89% for each market type, respectively.

Overall, the results suggest that in more symmetric markets, such as FBA-vs-FBA and FBM-vs-FBM, information sharing has pro-competitive effects. This leads to a redistribution of welfare from sellers to consumers, and Amazon benefits from increased fees due to higher transaction volume. However, in more asymmetric markets like the FBA-vs-FBM market, information sharing has anti-competitive effects, resulting in higher prices and reduced transactions at equilibrium. Both consumers and Amazon experience a decline in welfare, and social welfare is also reduced.

---

42Amazon, as the platform owner, earns profits from referral fees without engaging in direct market participation. In contrast to markets involving Amazon, vertical incentives are less significant because the referral fee primarily serves as a static modifier to sellers’ marginal costs.
Table A.6: Information Sharing with Third-Party Sellers, Third-Party-Only Markets

<table>
<thead>
<tr>
<th></th>
<th>15% Referral Fee</th>
<th>0% Referral Fee</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FBA-vs-FBM</td>
<td>FBA-vs-FBA</td>
</tr>
<tr>
<td>Panel A: Equilibrium Outcomes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>%Δ FBA Price</td>
<td>1.10</td>
<td>-3.34</td>
</tr>
<tr>
<td>%Δ FBA Sales</td>
<td>0.41</td>
<td>34.68</td>
</tr>
<tr>
<td>%Δ FBM Price</td>
<td>0.04</td>
<td>-0.85</td>
</tr>
<tr>
<td>%Δ FBM Sales</td>
<td>-15.94</td>
<td>2.22</td>
</tr>
<tr>
<td>Panel B: Profit and Welfare Change</td>
<td></td>
<td></td>
</tr>
<tr>
<td>%Δ Amazon Profit</td>
<td>-2.26</td>
<td>27.71</td>
</tr>
<tr>
<td>%Δ 3rd-Party Profit</td>
<td>2.21</td>
<td>-24.13</td>
</tr>
<tr>
<td>%Δ Consumer Welfare</td>
<td>-2.49</td>
<td>35.84</td>
</tr>
<tr>
<td>%Δ Social Welfare</td>
<td>-1.22</td>
<td>18.82</td>
</tr>
</tbody>
</table>

Note: Table A.6 presents the counterfactual analysis when Amazon shares its information with third-party sellers. Panel A shows the percentage changes in equilibrium prices and sales, while Panel B quantifies the changes in profits and welfare for Amazon, third-party sellers, and consumers. FBA-vs-FBM represents the market where an FBA seller competes with an FBM seller. FBA-vs-FBA represents the market where two FBA sellers compete with each other. FBM-vs-FBM represents the market where two FBM sellers compete with each other. Columns 1 to 3 correspond to the current 15% referral fee, and Columns 4 to 6 correspond to the case when the referral fee is reduced to 0%.