Competition, Obfuscation, and Price Dispersion in Online Markets: Evidence from Olist

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Section 1: Olist and the Structure of Online Competition

Olist is the leading Brazilian e-commerce platform that functions as a marketplace aggregator, which allows thousands of independent retailers to list and sell their products online (Crunchbase, n.d). Much of Olist's success comes from its business model as it is different from that of traditional e-commerce retailers. Rather than operating its own inventory, Olist connects third-party sellers to consumers, standardizes listings, and offers platform-level services such as payments, logistics integration, and customer support (CANVAS, 2024). It operates similarly to platforms like Amazon Marketplace or MercadoLibre, but with a large focus on the Brazilian market and strong integration into logistics and regional fulfillment infrastructure (Niwate, 2021). This makes Olist a compelling case for studying pricing behavior and market dynamics in the digital economy. Since multiple sellers can list the same product and each may choose different pricing and shipping strategies (CANVAS, 2024), Olist provides a rich environment for analyzing competition, price obfuscation, and price dispersion.

Section 2: Expectations from Classical and Modern Price Dispersion Models

The Bertrand model predicts that when consumers are fully informed and products are homogeneous, sellers will converge on a single market-clearing price. However, in many online markets, we continue to observe substantial price dispersion for identical products sold simultaneously by multiple vendors. This is largely because consumers are not fully informed, so when the perfectly informed consumer assumption is not met, we expect firms to escape the zero-profit outcomes as predicted by the Bertrand model. This paper investigates whether greater competition in online marketplaces, measured by the number of distinct sellers offering the same product, leads to higher price dispersion, and whether this relationship changes when sellers have the ability to shift pricing into less transparent cost components like shipping. Specifically, I test the hypothesis that competition reduces price dispersion only when consumers face transparent pricing, and that obfuscation tactics by sellers can undermine this effect in an online marketplace. I use detailed data from the Brazilian e-commerce platform Olist to test this question empirically and find that the answer depends critically on how prices are framed to the consumer.

Before examining the empirical results, it is helpful to outline the theoretical expectations based on classical models of price dispersion with search costs. The Stahl model (Stahl, 1989) offers a compelling framework for understanding how consumer search behavior influences pricing in competitive environments. In this model, firms produce a homogeneous good and simultaneously set prices. A share μ of consumers have nonpositive search costs ("shoppers") while the remainder face positive search costs ("non-shoppers"). The model shows that when even a small fraction of consumers face frictions in comparing prices, there is price dispersion in equilibrium despite the presence of competition. Additionally, the model yields a symmetric mixed-strategy equilibrium in which prices are drawn from a distribution that does not include marginal cost, and the amount of price dispersion decreases as the fraction of shoppers increases or as search costs fall. As μ approaches 1, the market converges to Bertrand competition. Conversely, as μ approaches 0, the market converges to the Diamond model (Diamond, 1971). This result bridges the extremes of the Diamond model (Diamond, 1971), where small search costs drive prices to monopoly prices, and Bertrand competition, where price equals marginal cost.

The Olist marketplace closely resembles the environment modeled in Stahl (1989). Products listed under the same product ID are homogeneous (in everything except price) and are sold by multiple competing vendors. Consumers, however, may face friction when comparing full prices (base price plus shipping fee) because Olist distributes its products across various online platforms and some of them display the base price and shipping fee separately. As a result, some consumers act as shoppers since they enjoy shopping and searching for the best price across platforms, while others behave like non-shoppers since their utility decreases as they search more. Thus, this leads us to the kind of segmented consumer behavior anticipated by the Stahl model (Stahl, 1989). In such a setting, we expect to have price dispersion in equilibrium even as the number of sellers increases, especially when search costs are increased because of price obfuscation.

The model proposed by Baye, Morgan, and Scholten (2004) complements this framework and provides a more direct application to digital platforms. Their model predicts that price dispersion increases with the number of competing sellers, even in the presence of price transparency. Sellers adopt mixed pricing strategies to attract both informed and uninformed consumers, and the presence of obfuscation (hidden fees, unbundled shipping, etc.) lets sellers maintain markups without appearing uncompetitive. In the context of Olist, this model suggests that price dispersion may persist not because consumers cannot observe prices, but because the price structure itself enables sellers to exploit cognitive limitations in consumer attention. Thus, we expect that price dispersion may increase with competition in transparent pricing environments (base price only), but not necessarily when obfuscation is possible (base price plus shipping).

Figure 1 illustrates this dynamic with a listing for a Motorola smartphone on the major Brazilian retailer Magazine Luiza (Magalu). Multiple sellers offer the identical product, but with dramatically different pricing structures. One seller from Olist lists the device for R$1,299.00 with R$26.04 in shipping fees, while another lists it for R$1069.90 with R$38.32 in shipping. Although the total price to the consumer differs significantly, the base price and shipping are shown separately, and buyers must calculate the true cost themselves. This separation enables price obfuscation to mask the actual cost and reduce the effectiveness of consumer price comparison. Thus, Olist is not only a facilitator of competition, but also a marketplace where strategic pricing behavior and consumer search frictions can manifest clearly.

Figure 1: An example listing of a Motorola smartphone on Magazine Luiza (Magalu), a major Brazilian retailer and one of Olist's key partners.

This paper finds that price dispersion increases with the number of sellers when considering base prices alone, but this effect disappears when total prices (including shipping) are considered. While this result appears to contradict the classical Bertrand prediction, it aligns closely with consumer search and obfuscation models such as Stahl (1989) and Baye, Morgan, Scholten (2004).

Section 3: Empirical Strategy and Methodology

To investigate the relationship between competition and price dispersion, I use data from over 100,000 Olist orders from 2016 to 2018. The dataset includes transaction-level information such as seller IDs, product categories, base prices, and shipping fees. I construct a panel dataset where each observation corresponds to a product-month combination (the sum of all transactions for a specific product within a given month) and calculate the normalized price dispersion (standard deviation divided by the mean price) across sellers for each product-month. To ensure the quality of the analysis, I exclude product-months with only 1 seller (because there is no competition) and filter out data with missing or zero values for key variables such as price or shipping.

I merge this cleaned dataset with seller counts and product category data to examine variation across time and market segments. Summary statistics[1] show that, after filtering out product-months with only one seller, the average product-month in the sample has 2.11 sellers. Additionally, 99.66% of orders include a non-zero shipping fee, which indicates that shipping is frequently used and may serve as a channel for price obfuscation.

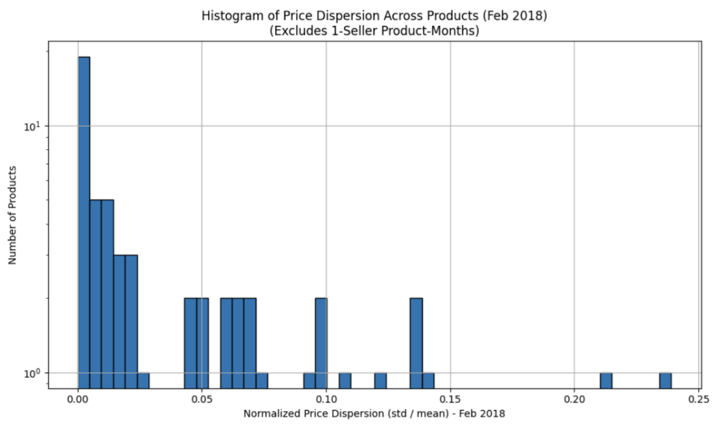
I estimate fixed-effects panel regressions with controls for product category and time to isolate the effect of seller competition. Two specifications are used: one based on the base price alone, and the other using the total cost to the consumer (base price plus shipping) to assess how transparency affects pricing dynamics. The empirical model is specified as:

$$PD_{it} = \alpha_j + \alpha_t + \beta \cdot sellers_{jt} + \varepsilon_{jt}$$

where PD_{it} is the price dispersion for product i in month t, α_j is a fixed effect for product category, α_t is a fixed effect for time, and $sellers_{jt}$ is the number of sellers offering product j in month t.

I do not claim a causal interpretation of the coefficient $\widehat{\beta}$, as seller entry may itself be endogenous to expected pricing strategies. Instead, the fixed-effects model is used to estimate conditional correlations while controlling for unobserved heterogeneity across product categories and time periods.

Figure 2: Histogram of Normalized Price Dispersion Across Products (Feb 2018)

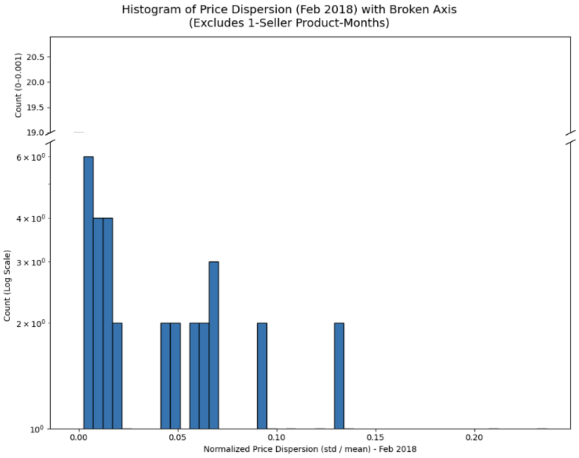


Before turning to the regression analysis, it is useful to describe the overall structure of price dispersion in the dataset. Figure 2 presents a histogram of normalized price dispersion (standard deviation divided by mean price) across products with more than one seller selling the same product using Olist in February 2018. The distribution remains highly right-skewed, with the majority of products showing very low dispersion and a long tail of products with more substantial price variation. While the sample size is relatively small with 57 products, the histogram still reveals dispersion in a subset of the market. To improve visibility of the lower tail, Figure 3 displays a version of the histogram with a broken vertical axis. This highlights that most multi-seller products still cluster in the lowest dispersion bin

[1] Provided in code

(between 0 and 0.001), though several exhibit significantly greater variability. These descriptive patterns suggest that while pricing is relatively uniform across many listings, likely due to platform constraints or price coordination, a great portion of products do experience competitive price differentiation. These insights help motivate the regression analysis that follows, which investigates whether variation in seller competition explains these observed differences in price dispersion.

Figure 3: Histogram of Normalized Price Dispersion Across Products with Broken Axis (Feb 2018)



Section 4: Empirical Findings and Interpretation

The analysis reveals that the effect of competition on price dispersion depends significantly on how prices are presented to consumers. When using base price alone, the fixed-effects panel regression shows a strong and statistically significant positive relationship between the number of sellers and price dispersion ($\widehat{\beta} = 0.0091, p < 0.0001$; see Table 1). This estimate implies that each additional seller is associated with a 0.91 percentage point increase in normalized price dispersion on average. This result aligns with theoretical models that predict sellers engage in differentiated pricing strategies to attract inattentive consumers in competitive environments.

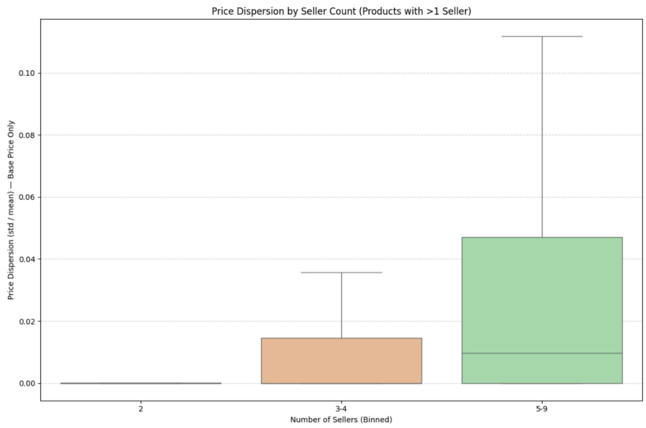
Table 1: Panel Regression Results for the Effect of Number of Sellers on Price Dispersion Using Base Price Only

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
num_sellers	0.0035	0.0006	5.7783	0.0000	0.0023	0.0046

This relationship is also visually supported in Figure 4, which displays a boxplot of normalized price dispersion across product-months, binned by the number of sellers. The chart shows a clear upward trend in the dispersion of base prices as the number of sellers increases, especially between the 2–4 and 5–9 seller bins.

Figure 4: Distribution of Price Dispersion by Number of Sellers (Base Price Only)



However, this pattern disappears when price dispersion is calculated using total cost (base price plus shipping). In this context, the coefficient on seller count becomes statistically insignificant ($\widehat{\beta} = 0.0004, p < 0.81$; see Table 2). This estimate implies that each additional seller is associated with a 0.0004 percentage point increase in normalized price dispersion on average, which is almost nothing. This demonstrates that the apparent competitive effect vanishes when sellers can shift part of the price into less visible components like shipping.

Table 2: Panel Regression Results for the Effect of Number of Sellers on Price Dispersion Using Base Price + Shipping

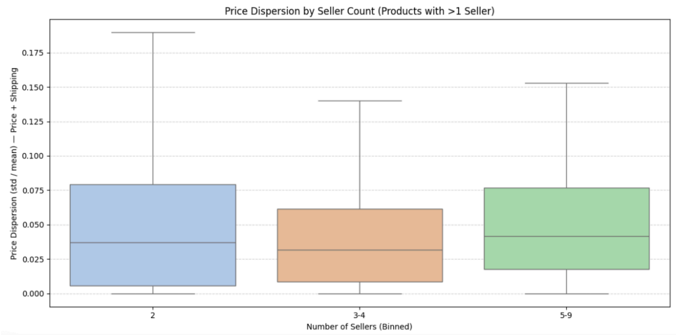
Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
num_sellers	0.0012	0.0015	0.8322	0.4054	-0.0017	0.0042

Figure 5 visualizes this result by showing the distribution of normalized price dispersion across different seller count bins when using total cost. Unlike the base price case, there is no clear upward trend in dispersion as the number of sellers increases.

This divergence underscores the role of price obfuscation even though sellers don't individually control shipping fees. While competition appears to increase price dispersion when prices are fully visible, the separation of base price and shipping weakens this effect by making it harder for consumers to assess the total cost. These findings support the predictions of the Stahl model (Stahl, 1989), which shows that even modest search frictions can sustain price dispersion in equilibrium. Olist's pricing structure, where base and shipping fees are mostly displayed separately across different marketplace platforms, mirrors this environment by segmenting consumers into those who compare total costs and those who rely on visible base prices alone.

Figure 5: Distribution of Price Dispersion by Number of Sellers (Base Price + Shipping)



The results also align with the model from Baye, Morgan, and Scholten (2004), in which sellers use pricing strategies that cater to both informed and inattentive buyers. Their prediction that price dispersion may rise with the number of sellers is supported in the base price model. However, the total price results indicate that once part of the cost becomes less visible, the competitive effect decreases, as some consumers fail to account for hidden fees.

An important observation is that both the median and range of normalized price dispersion are generally greater when shipping costs are included than when using base price

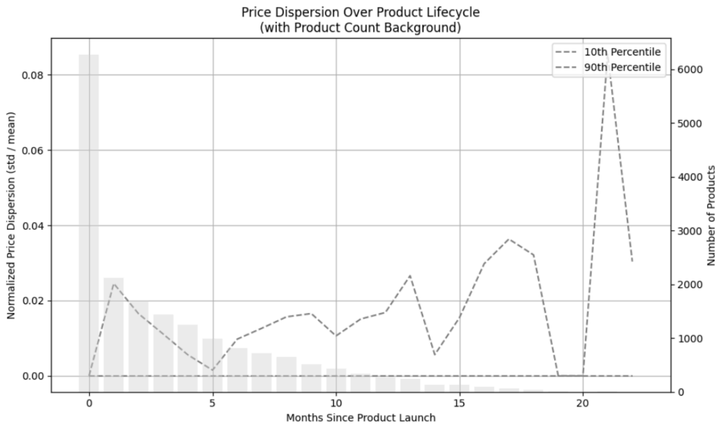
Table 3: Summary Statistics of Price Dispersion (Base Price vs. Base Price + Shipping Cost)

seller_bin	num_products	base_median	base_min	base_max	shipping_median	shipping_min	shipping_max
2	3908	0.0000	0.0000	0.4202	0.0370	0.0000	0.6906
3–4	1016	0.0000	0.0000	0.2700	0.0319	0.0000	0.4878
5–9	162	0.0097	0.0000	0.1919	0.0417	0.0000	0.1530

alone (see Table 3). This suggests that obfuscation not only conceals true prices, but also allows platforms or sellers to sustain or amplify variation in total cost across consumers. Even though the marketplaces (not sellers) are setting these shipping costs, this still increases the difficulty in evaluating prices.

In addition to how prices are presented, dispersion may also evolve as products remain on the platform. Figure 6 plots the 10th and 90th percentiles of normalized price dispersion by the number of months since a product first appeared on Olist. The gray bars in the background represent the number of products observed at each lifecycle stage. The figure shows that dispersion is generally low in the early months after a product is listed on the platform, but becomes more variable as it remains on the platform. This could reflect experimentation in pricing over time, reduced competition as sellers exit, or consumers' declining ability to compare older listings. However, product counts drop steeply after month 5, so the widening in later percentiles should be interpreted cautiously. Overall, this analysis reinforces the idea that dispersion is shaped not only by competition and obfuscation, but also by how long a product remains active in the marketplace.

Figure 6: Price Dispersion Over Time on Olist (with Product Count in Background)



Ultimately, these findings challenge the classical Bertrand prediction that increased competition compresses prices. Instead, they reinforce more nuanced models of online marketplaces where search frictions, price framing, and platform rules mediate how competition affects consumer outcomes.

Section 5: Limitations

While this study offers empirical insights into the relationship between competition and price dispersion in online marketplaces, several limitations warrant discussion.

First, the analysis does not make a causal claim about the effect of seller count on price dispersion. The number of sellers offering a product may be endogenous to expected pricing behavior if, for example, products with higher expected profit margins or consumer demand volatility inherently attract more sellers. Although fixed effects for product category and time are included to control for unobserved heterogeneity, omitted variable bias may be a concern since no external instrument is used to address this endogeneity.

In addition, the assumption that sellers independently set both price and shipping fees may not hold uniformly across platforms. For example, one consumer may get free shipping from Amazon Prime while one consumer may not, even if the marketplace sets the shipping price to be greater than $0. There may also be discounted shipping if a customer spends a certain amount of money on the platform, so sometimes the shipping cost that the customers paid may not be the shipping cost that was set, leading to inaccurate calculations of price dispersion.

Lastly, while fixed effects help control for broad temporal and category-level variation, unobserved product-level heterogeneity remains a challenge. Differences in item condition, seller reputation, bundling, or listing quality may contribute to price variation across sellers in ways not fully captured by the model.

Section 6: Conclusion and Future Work

This analysis examined the relationship between the number of sellers and price dispersion in an online marketplace, considering both product price alone and total price including shipping. Using panel data and fixed effects, we observed how competition shapes pricing variation across different seller environments.

In future iterations, incorporating consumer behavior data (e.g., browsing, responsiveness to shipping fees) would allow for a better understanding of dynamics on the demand side. Adding more granular product or seller-level features (e.g., brand strength, fulfillment methods, or return policies) could also improve the explanatory power of the model. In addition, future work should aim for causal inference, perhaps through natural experiments or instrumental variables, to better isolate the effects of seller competition.

When it comes to platform design, it remains challenging to determine what constitutes an "optimal" configuration. Marketplace outcomes reflect trade-offs among multiple goals including price transparency, consumer satisfaction, and revenue maximization, so these goals often conflict. Moreover, platform interventions such as online ads can have complex effects. In studies on online advertising and social network design, evaluating welfare in digital platforms is inherently difficult due to the many interdependent stakeholders. Defining an optimal design requires not just data on prices and sellers, but also models that account for ecosystem-level interactions among users, sellers, and the platform itself. For platforms like Olist, designing effective marketplace structures will not only depend on seller behavior, but also an understanding of how platform design choices, consumer incentives, and strategic interactions collectively shape pricing dynamics.

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