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Popularity and Transaction Prices as Drivers of Price Dispersion on Two-Sided Digital Platforms

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ABSTRACT

Objective: the increase in e-commerce transactions has resulted in the understanding of the dynamics of pricing in digital marketing in B2B and B2C environments. This is crucial for capturing buyer preferences and influencing store profitability. Our empirical study reviews how factors such as product popularity, transaction volume, price adjustments, and shipping time influence price dispersion on two-sided e-commerce platforms. **Methods:** panel data regression models were estimated using a comprehensive dataset from different product categories. **Results:** the main findings reveal a negative influence of product popularity on price dispersion, suggesting stronger competition and buyer engagement as potential drivers. A positive association between transaction volume and price dispersion also highlights the effect of efficient marketing strategies. **Conclusions:** the research is important because it sheds light on variables that are significant for transactions on digital two-sided platforms, such as product popularity. It also assists managers in efficiently planning pricing strategies, product promotion, and reputation management.

Keywords:
digital marketing; price dispersion; product popularity; transaction prices; two-sided platforms

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INTRODUCTION

Two-sided markets are large and profitable on a global scale. In 2023, Amazon and eBay were the most popular e-commerce and online shopping platforms (Statista, 2023a), generating combined revenues of 584.89 billion dollars (FourWeekMBA, 2024). The number of transactions in e-commerce is expected to increase even further. Market statistics published by Forbes (2023) reveal that 62% of consumers make up to five online purchases a month. At this rate, the volume of e-commerce sales is estimated to grow by 56% over the next few years, reaching around 8.1 trillion dollars by 2026 (Statista, 2022). Price dynamics and pricing decisions on two-sided platforms are key factors, as they influence buyer preference and affect store profitability (Choi & Mela, 2019).

According to the existing literature, studies on price dispersion have focused on reviewing posted prices because of the shortage of transaction data (Grewal et al., 2010). In fact, many studies on pricing are carried out using purchase intentions collected through questionnaires (i.e., Maia et al., 2019). This, however, may skew estimates of the actual dimension of price dispersion (Ghose & Yao, 2011) as it disregards consumer behavior as a result of the final or listed price (Zhao et al., 2015). That is because, in some situations, the price paid and the quantity purchased are determined by a transaction process involving an interaction between buyers and sellers (Bruno et al., 2012). Two-sided platforms, such as eBay, are online shopping environments that allow this type of mediation (Choi & Mela, 2019) and generate transaction price data ensuing from the process of bargaining for the best offer (Backus et al., 2020). Recent studies also show that strategies such as cashbacks may intensify price dispersion in certain market contexts, adding a layer of complexity to reviews (Oliveira et al., 2024).

Theoretically, understanding transaction price dispersion is important because it provides insights into consumer behavior and market dynamics. Price dispersion reflects the interactions between sellers and buyers, comprising elements such as competitive strategies, consumer preferences, and dynamic price adjustments. For two-sided platforms, it also expands knowledge about digital markets, as transaction prices are the outcome of specific interactions that differ from those of traditional markets (Backus et al., 2020; Zhao et al., 2015).

Literature has addressed dispersion in transaction prices (e.g., Ghose & Yao, 2011; Zhao et al., 2015; Zhuang et al., 2018). However, there are gaps in the understanding of platform-based markets (Perren & Kozinets, 2018), and there is a need to identify the factors that drive price dispersion in this type of market, which brings together several categories of heterogeneous products. Studying price dispersion in heterogeneous markets helps challenge and complement what we already know about homogeneous markets, such as books (Brynjolfsson & Smith, 2000; Zhuang et al., 2018), offering a broader view of e-commerce complexities.

Product differentiation affects price dispersion (Pan et al., 2002), which is often a result of seller heterogeneity (Lach, 2002). This differentiation on two-sided platforms may influence product popularity. This is a specific characteristic (Zhu & Zhang, 2010) that increases the likelihood of purchase and total sales (Castro et al., 2013; Sevilla & Townsend, 2016), demonstrates product quality (Hanson & Putler, 1996), and influences consumer preference (Powell et al., 2017). However, although it is an important response variable, it is not clear how product popularity affects price dispersion, since it is an indication of consumers' direct interest (Lai et al., 2019; Puzakova & Kwak, 2017) when prices are checked as a cognitive rule before making a purchase decision (Bown, 2007; Bunn, 1993).

This paper aims to fill this gap and explores product heterogeneity as a key factor in the literature on price dispersion in digital environments. The primary objective is to understand the influence of product popularity on transaction price dispersion on two-sided platforms. In this study, product popularity is based on the ratio of users adding a given product to their wish list (Zhao et al., 2015). Popularity reflects consumer preferences ensuing from evaluations and reviews of previous information issued by other users sharing similar objectives (Jang & Chung, 2021).

Panel data regression models with random effects were estimated, employing a sample of exclusive and comprehensive data from transactions on one of the largest online shopping platforms in the global market. Price dispersion varies between product categories (Chen & Scholten, 2003). Longitudinal data were organized in a panel structure for nine metacategories, comprising 219 subcategories (more refined categories) over the years 2012 and 2013. During that period, it was found that these subcategories individually covered a maximum average of 30,709 transactions, with a maximum average of 27,772 buyers. The data richness allowed focusing the review on transaction price dispersion while making comparisons with the posted price.

Underlying mechanisms between transaction price dispersion and product popularity were tested and recorded, controlling for the role played by the course of time and product heterogeneity at the metacategory level. This research provides consistent results for price dispersion theory. Firstly, it finds that product popularity negatively affects price dispersion on two-sided platforms. A potential explanation lies in the fact that, over time, as a product becomes more popular, competition increases (Baye et al., 2004) and price distribution becomes visible to more buyers. Secondly, it identifies that the number of transactions over time has a positive association with price dispersion. Managers and marketers working on two-sided platforms can encourage price discounts and bargaining, as these are marketing actions that affect price variation and boost the quantity transacted. Thirdly, it also observes that price adjustment has a positive influence on price dispersion levels. However, as these changes are more frequent in the short term, their impact on price changes is lower than that of more regular, low-frequency changes (Bronnenberg et al., 2006; Brynjolfsson & Smith, 2000).

In the next sections, we develop the theoretical framework for pricing in two-sided markets. We define four hypotheses about the relationship between price dispersion and product popularity and other underlying drivers. The next section provides information about the methods used and presents the results. The paper ends with a discussion about the implications of the findings and offers directions for future research.

THEORETICAL FRAMEWORK

Digital marketing, price, and competition on two-sided platforms

Digitalization has brought greater attention to platform-based B2B (business-to-business) and B2C (business-to-consumer) relations in the field of digital marketing. In B2B marketing, for example, the dynamics of relationships between suppliers and customers involve the co-creation of superior value, which would not be achieved by suppliers alone (Hofacker et al., 2020). In B2C marketing, on the other hand, the focus is on attracting consumers to autonomously purchase on digital platforms, with no need for direct interaction with sellers, promoting a more realistic and independent consumer experience (Desai & Vidyapeeth, 2019).

Two-sided platforms, also known in marketing and economics literature as two-sided markets (Lin, 2020) and marketplaces (Vieira et al., 2019, 2022; Viswanathan et al., 2010), are websites that facilitate this technological interaction of exchanges between market players holding similar positions (Perren & Kozinets, 2018), an empirical context of e-commerce (Sen et al., 2023). The term two-sided refers to a dual perspective that includes both the supply and demand sides of the market, i.e., a two-sided platform that places buyers and sellers on opposite sides (Choi & Mela, 2019), intermediating end-to-end relationships (Vieira et al., 2019).

Two-sided markets play a key role in the global economy. Literature shows that they have contributed to the internationalization of small businesses (Singh et al., 2023), the boosting of subsistence markets (Sarker et al., 2022; Viswanathan et al., 2010), the leveraging of media platforms (Lin, 2020), the investigation of exploitation in service platforms (Zhou et al., 2022), the creation of value for ride-sharing platforms (Saxena et al., 2020), among others. Platforms are also characterized by modularity in their structure, allowing for more flexible business models (Singh et al., 2023), including those arising from innovative and entrepreneurial initiatives (Nambisan et al., 2019).

The growth of two-sided markets brings challenges and inconsistencies that raise managerial concerns. Zhou et al. (2022) outline that the so-called 'platform exploitation' may have serious consequences, leading to the defection of customers from service platforms. This is because service platform agents may exhibit opportunistic behavior, violating the rules by carrying out transactions outside the platforms to avoid paying fees. On digital platforms such as Amazon and eBay, this type of deceitful practice has serious impacts. Not only does it result in substantial drops in market share, but it also negatively affects consumer confidence in brands competing in the same product category (Bei & Gielens, 2022). Perren and Kozinets (2018) address concerns about the security of transactions on two-sided platforms, as these markets transfer security responsibility to the players, institutions or algorithms ruling the platforms. This can make it difficult to manage the risks of co-presence in these environments. Auer and Petit (2015) have shown that the theory of two-sided markets also highlights concerns about antitrust policy in digital markets, aimed at preventing the establishment of monopolies that could harm competitiveness. Economic activism in two-sided markets also enters the debate, generating relevant concerns about equality and respect in consumer society (Branchik & Davis, 2009).

The nature of two-sided markets allows for greater competition, which can occur both between internal users of the platforms and between the platforms themselves. For classical marketing theory, competition is the result of companies with interdependent objectives adapting to the scarce market environment (Alderson, 1937). This principle applies both to conventional markets aimed at attracting buyers with low prices and greater perceived usefulness and to two-sided markets, where you can act on both sides, trying to reach both buyers and sellers (Roson, 2005). For example, eBay may foster multidimensional competition by choosing whether to reduce its fees for sellers, for buyers, or for both sides.

Competition on two-sided platforms decreases sellers' revenue (Choi & Mela, 2019), since companies have to spend more on constantly monitoring and adjusting their pricing strategies to remain competitive. The theory of two-sided markets suggests that price has a negative effect on the platforms' profitability (Roson, 2005) because consumers are price-sensitive. On the other hand, when competition increases and sellers start paying higher advertising rates, for example, this has a positive impact on the platforms' profitability (Choi & Mela, 2019). Thus, there is a need to establish balanced prices for the products sold.

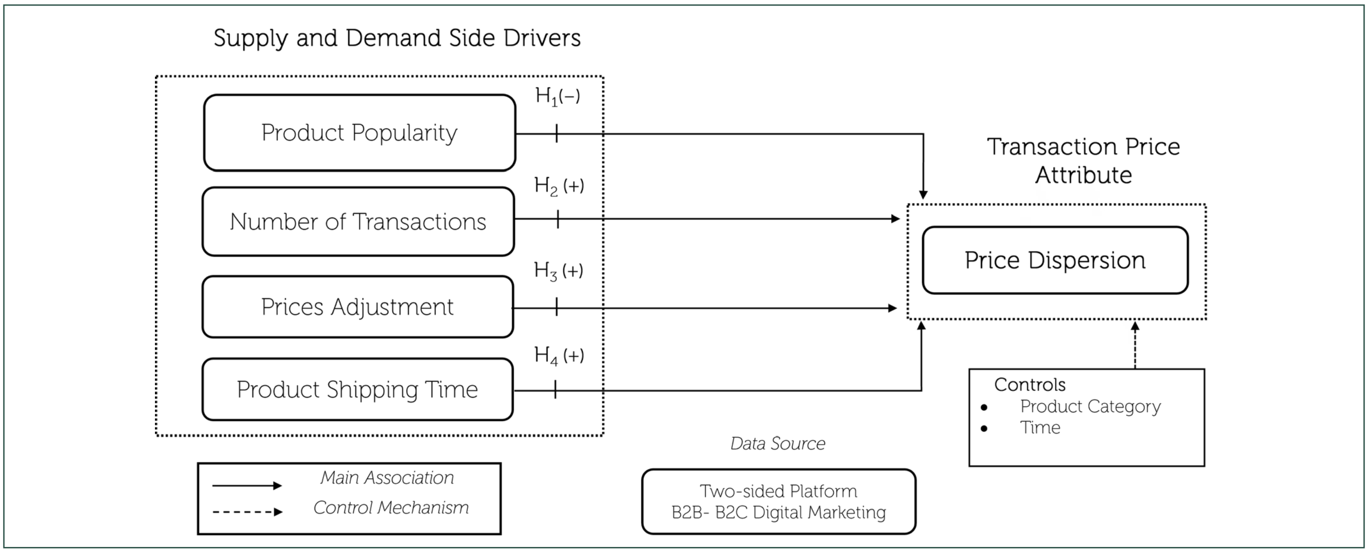
Prices on platforms are determined by the intersection of supply and demand. It is a dynamic and consociational environment where "total production is influenced by the distribution of prices between the many groups" (Auer & Petit, 2015, p. 426) involved. In marketing, consociality is the virtual presence of social players in a network that allows interaction between them (Perren & Kozinets, 2018). This occurs when buyers and sellers collaborate to establish the equilibrium price of a product or service.

In this sense, demand functions are more suitable than those underlying utility for understanding equilibrium prices because market demand details the total demand of buyers for goods and services in the economy, considering all existing prices (Scarf, 1982). On two-sided platforms, the equilibrium price reflects the point at which the quantity demanded by buyers corresponds to the quantity offered by sellers, creating an equilibrium in the market (Stahl et al., 2017). This stability is important to efficiently allocate resources and ensure that both buyers and sellers cash in on transactions.

Thus, our research offers relevant contributions to the theory of two-sided markets by addressing some of its limitations. For example: (1) when it highlights the differentiation of effects on price and demand, as this introduces new perspectives going beyond the share of value as the main performance variable (Bei & Gielens, 2022). Measures such as transaction price dispersion and product popularity, based on consumer evaluation and perception, help to develop strategies to increase store profitability and seek solutions to trust-related problems on digital platforms, such as opportunism (Perren & Kozinets, 2018); (2) when using actual data from a market that is known to be two-sided according to the theory of two-sided markets, such as eBay. This is crucial, as the mistaken categorization of markets as two-sided, when in fact they only present indirect externalities, may lead to theoretically inconsistent results (Auer & Petit, 2015); (3) by highlighting consumer ratings as an essential variable for assessing the performance of companies operating on two-sided platforms. This involves delivery time, which is a price determinant, varying depending on the location of market players (Gao et al., 2017).

A framework to analyze the impact of two-sided market characteristics on price dispersion

Considering the specificities of two-sided platforms, we propose a theoretical framework (Figure 1) establishing the positive and negative influences of attributes of these markets on the transaction price dispersion. The product popularity variable plays a primary role in such relations, and stems from the massive process of consumer evaluations. Other variables, such as the number of transactions, price adjustment, and product shipping time, are identified as key attributes involving both the supply and demand sides of these platforms. The variables that control variability between product categories and time effects influence the proposed associations from the supply and demand side drivers.



Source: Developed by the authors.

Figure 1. Theoretical framework for price dispersion on two-sided platforms.

The framework proposes testing four hypotheses aimed at evaluating associations between the main drivers on the supply and demand sides of two-sided platforms and the transaction price attributes, represented by price dispersion measures. Testing these relationships is relevant to the literature, as companies operating on two-sided platforms heavily invest in marketing strategies (Sridhar et al., 2011), and the commercial transactions established are pivotal to the economy (Choi & Mela, 2019), as they provide greater reach for sellers and expand consumers' power of choice.

Effects of product popularity and number of transactions

In e-commerce, the number of times a product has been added to the wish list or commented on shows the market's interest in it (Zhao et al., 2015), i.e., the consumer is signaling that they want to buy it. This usually occurs after submitting the product or a brand to an information filter based on the evaluations of other buyers, seeking for quality or reliability (Zhu & Zhang, 2010).

Products that receive many reviews become popular (Powell et al., 2017) and are desired by consumers sharing similar interests. Jang and Chung (2021) show that product popularity comes on the scene in two ways: through the actions of others, when buyers use information provided by other people to minimize the uncertainty of their decisions; and through consumer evaluations, representing a summary of the buyers' aggregate preference for a given product.

Popular products have, on average, more offers available on the market (Baye et al., 2004) and information on popularity is a marketing tool that reinforces sales trends (Tucker & Zhang, 2011). However, this can add complexity to consumer decision-making. Marketing literature shows that consumers use product popularity as a quality indicator to support their decisions when presented with a range of alternatives (Hanson & Putler, 1996). If alternatives are accompanied by multiple attributes and information, consumers tend to use a non-compensatory strategy to simplify their decision-making and start to consider the most important attributes, such as the product price (Bown, 2007).

This is a significant process because sellers' behavior varies in the market and influences the characteristics of their products, making them differentiated (Lach, 2002) and influencing price dispersion (Chen & Scholten, 2003). As e-commerce matures and online shopping increases, product popularity and price dispersion have become increasingly important factors for consumers in their purchasing decisions (Wijaya et al., 2019). In a causal relationship, the literature shows that product popularity is a determining factor in price dispersion (Baye et al., 2004).

The popularity of a product is believed to mitigate price dispersion, since it makes the product more targeted and more competitive in the market. If popularity takes shape when there is greater customer engagement when evaluating a given product (Jang & Chung, 2021), the economic theory envisages that customer engagement reduces price dispersion, with an amplifying impact only when a product has a competitive advantage over another (Cohen, 1998).

On the one hand, consumers tend to prefer products with lower price dispersion, as this suggests that they are getting a good deal compared to other options available (Bouichou et al., 2022). On the other hand, when price dispersion is high, consumers may challenge both the quality and value of the product, leading to hesitation in purchasing, even if the item is popular. This hesitation occurs because consumers are looking for a guarantee that they are getting the best possible deal for the price they want (Putra & Belgiawan, 2023). As product popularity increases, so does the number of companies marketing it (Baye et al., 2004) and consumer engagement (Cohen, 1998). This process reduces price dispersion, narrowing the distribution of values. In short, popular products have more limited price dispersion, since greater consumer engagement facilitates a more accurate perception of fair market value, and puts pressure on sellers to offer more aligned prices. Thus, it is assumed that:

> H1: Product popularity is negatively associated with price dispersion on two-sided platforms.

The presence of multiple networked (Perren & Kozinets, 2018) players allows two-sided platforms to bring together buyers and sellers with local and global identities (Gao et al., 2017). This has an impact on the sales metrics of large platforms such as Amazon and eBay, which account for large volumes of transactions (Statista, 2023b). The number of transactions represents the effect of the order on price dispersion (Ghose & Yao, 2011), so it is the result of the quantity bought or transacted.

Previous research has shown that the quantity purchased varies according to price levels. Bruno et al. (2012) identified that consumers tend to purchase smaller quantities when the price of the product exceeds the reference price. In addition, the discounts usually applied by a brand in specific product categories influence the consumer's decision and the quantity purchased. If a buyer perceives that the brand is offering a lower discount than usual, they may interpret that purchasing at that time is not advantageous, resulting in a reduction in the quantity stocked against a more significant discount (Krishna et al., 1991).

On the eBay platform, for example, buyers and sellers can strongly negotiate to achieve the best offer, using the 'best offer' mechanism. On this platform, bilateral experience plays a pivotal role in the final price, as more experienced buyers can negotiate lower prices, while experienced sellers can get higher final prices (Backus et al., 2020). Considering both the discounts applied to prices and the final prices resulting from negotiations, the quantity transacted is assumed to have a positive effect on price variation. Thus, it is assumed that:

H2: The number of transactions is positively associated with price dispersion on two-sided platforms.

Effects of price adjustment and shipping time

In the standard view of marketing theory, companies make price adjustments to dynamically adapt to changes in demand, supply, cost structure and market segmentation (Alderson, 1937; Srinivasan et al., 2008). These operations take place more quickly in e-commerce, keeping up with the fast pace of that market (Brynjolfsson & Smith, 2000). Despite the challenges and complexities of changing prices in the digital environment, due to the transparency of information, adjustments are marketing tools that help sellers effectively manage market changes and improve their profitability (Chen et al., 2022).

Adjustments occur when sellers list a product at a certain price and, over time, make changes (Zhao et al., 2015). This is a common practice in e-commerce due to lower menu costs incurred by sellers when they change a posted price (Brynjolfsson & Smith, 2000). Compared to conventional markets, making price adjustments on the Internet appears to be easier, as the managers' main action consists of simply changing the price information in a database. However, the literature shows that companies incur management costs to collect price information, make decisions, and assertively communicate these price changes in the market (Böheim et al., 2021).

Specifically, sellers set product prices at the beginning of each replenishment cycle and then decide whether or not to change prices (Chen et al., 2022). This results in consumers buying products at both the initial price and the adjusted price. The specialized literature has mostly reviewed posted prices (Bronnenberg et al., 2006; Brynjolfsson & Smith, 2000) or past prices (Srinivasan et al., 2008) that typically consider consolidated prices directly in the price variable. This approach, however, does not fully capture consumer behavior in relation to the final price (Zhao et al., 2015), mainly in digital environments.

This study fills this gap, as it adopts a different perspective, focusing on the direct relationship over time between menu cost and price dispersion on two-sided platforms. Here, the price data used are based on the transaction price, which reflects the adjustments perceived and influenced by consumers. These platforms have unique dynamics, such as bargaining processes and rounds of negotiation (Backus et al., 2020; Zhao et al., 2015), which often explain why transaction prices differ from published prices (Ghose & Yao, 2011). The purchase of price-adjusted products affects price dispersion (Zhao et al., 2015). The study by Bronnenberg et al. (2006) showed that the greatest impact on price dispersion does not stem from the more frequent adjustments made by sellers in the short term but rather from slower price movements, which have a sharper impact on price variation, mainly when it involves price discounting strategies.

It is assumed that on two-sided platforms price adjustments increase over time. Böheim et al. (2021) recently showed that the influence of menu costs on price variation weakens in the long term. When the cost structure associated with price adjustments is low and benefits are high, it is more interesting to set prices based on demand (Srinivasan et al., 2008). Therefore, as it becomes less costly to adjust prices (Brynjolfsson & Smith, 2000), sellers will increase the frequency of adjustments, entailing a positive influence on price variation. Thus, it is assumed that:

H3: Price adjustments are positively associated with price dispersion on two-sided platforms.

In the bilateral exchange market, platforms play a role similar to that of a hub, connecting sellers to buyers. Hubs are intermediaries that facilitate exchanges in a marketplace network (Vieira et al., 2019), creating "two discrete and bidirectional flows," as exemplified by actor ↔ two-sided platform ↔ actor (Perren & Kozinets, 2018, p. 27). On a global scale, this allows for the co-presence of actors with different local and global identities, impacting price dispersion levels, since an Internet purchase commonly involves specific shipping issues (Brynjolfsson & Smith, 2000).

Different geographical locations influence price behavior on both the supply and demand sides. On the supply side, companies can create tactics aimed at targeting buyers' local identity, decreasing sensitivity to price without necessarily positioning the brand as local

(Gao et al., 2017). On the demand side, buyers can use electronic channels, such as webcasts, to access prices further away globally, especially when they notice that these prices are lower in more remote geographical facilities than in local facilities (Overby & Forman, 2015).

In e-commerce, there is greater freedom for consumer preferences to prevail. However, buying from geographically more distant locations influences the time it takes to ship the product. Previous research showed that patient buyers may choose the slowest shipping method when they are willing to wait a little longer to pay less in freight and handling fees (Backus et al., 2020) and that the variation in shipping and handling influences price perception (Jiang & Rosenbloom, 2005).

Thus, electing the slowest method impacts price dispersion because (1) the product takes longer to ship and, most importantly, (2) prices of the most affordable packages vary more than the shortest-time option, which usually has a standard price. Therefore, although e-commerce lowers transaction costs (Overby & Forman, 2015), geographical location is a factor that affects sellers' pricing (Zhuang et al., 2018), especially when shipping times are longer for the delivery of products. This happens, for example, when products need to be shipped to more remote geographical locations in relation to the seller's local identity. Thus, it is assumed that:

> H4: The option of longer product shipping has a positive association with price dispersion on two-sided platforms.

METHOD

Sample and data collection

We organized a panel sample representing 10% of the longitudinal data originated from a dataset of 88 million transactions between buyers and sellers carried out on the eBay platform in the United States. Data were collected between May 31, 2012, and June 1, 2013, and made available by Backus et al. (2020). In terms of global reach and scale, eBay is present in more than 190 markets, with 132 million active buyers and 1.9 billion active bids, and is one of the most accessed platforms in the world, with 1.2 billion accesses (eBay, 2023; Statista, 2023b). It also stands out as the largest company in the field of online auctions, operating B2B (business-to-business) and B2C (business-to-consumer) transactions. Its data have been widely used in research in the field of digital marketing (Backus et al., 2020; Massad & Tucker, 2000).

The original dataset is based on metacategories containing more refined categories, known as (anonymized) subcategories, as shown in Table 1. Given the heterogeneity of products and to meet the objectives of this research, the following filtering was applied: (1) only the category of new products, (2) only subcategories with more than 500 observations (annual transactions) to obtain a more consistent data distribution between the years 2012 and 2013, and (3) only observations containing both the posted price and the transaction price. This procedure resulted in a short (N = X, T = Y, where X > T) and balanced panel, containing a final sample of 438 observations spread over nine metacategories, according to the nomenclatures defined by eBay.

Table 1. Number of observations and frequencies for metacategories and subcategories.

Metacategories	Subcategories 2012	Subcategories 2013	Total	Proportion
1. Books	5	5	10	2.3%
2. Business and Industrial	20	20	40	9.1%
3. Collectibles	36	36	72	16.4%
4. Computers, Tablets and Networks	21	21	42	9.6%
5. Health and Beauty	22	22	44	10.0%
6. Home and gardening	24	24	48	11.0%
7. Jewelry and Watches	22	22	44	10.0%
8. Sporting goods	32	32	64	14.6%
9. Toys and Hobbies	37	37	74	16.9%
Total	219	219	438	100.0%

Note. Elaborated by the authors. Subcategories and products are anonymized in the source database.

Each subcategory has a unique eBay Identifier (ID) that identifies it as unique in the dataset. The inclusion of multiple product categories improves reviews at the product level and adds robustness to results since some categories are more homogeneous than others (Ghose & Yao, 2011).

Measures and variables

The dependent variables are the price coefficient of variation (CV) and the percentage price difference (DifPercent). These measures are commonly used in the literature to reflect price dispersion (e.g., Ghose & Yao, 2011; Wang et al., 2020; Zhao et al., 2015). The richness of the data extracted from the eBay platform lies precisely in the possibility of measuring both the posted and the transaction prices. Considering that each subcategory has a 'n' number of products, the CV is calculated by the ratio of the standard deviation of prices in the product list in each subcategory to their average price, i.e., $\frac{\sigma}{\bar{P}}$. Meanwhile, DifPercent is obtained by subtracting the maximum price of the product list from the minimum price, divided by the average price, i.e., $\frac{p^{max} - p^{min}}{\bar{P}}$. Table 2 provides a detailed description of the main units of analysis, the dependent and explanatory variables used in the models in this study, as well as the theoretical background justifying the use of these analytical measures.

Table 2. Definitions and measures of the variables in this study.

Variable	Description	Type	Attribution	Theoretical background
CV	Price coefficient of variation	Quantitative	Dependent	Backus et al. (2020) Bronnenberg et al. (2006) Brynjolfsson and Smith (2000) Böheim et al. (2021) Ghose and Yao (2011) Hanson and Putler (1996) Jiang and Rosenbloom (2005) Overby and Forman (2015) Oliveira et al. (2024) Perren and Kozinets (2018) Tucker and Zhang (2011) Zhao et al. (2015) Zhuang et al. (2018) Srinivasan et al. (2008)
DifPercent	Percentage price difference	Quantitative	Dependent	
Product popularity	Average number of users who have added the product to their wish list	Quantitative	Explanatory	
Transaction	Number of transactions between buyers and sellers	Quantitative	Explanatory	
Prices adjustment	Percentage of how many times the seller modified the posted price during the period in which the item was listed	Quantitative	Explanatory	
Product shipping time	Average maximum shipping time (in hours) for the slowest shipping option for the product	Quantitative	Explanatory	
Buyers	Number of buyers per subcategory	Quantitative	Explanatory	
Dummy: Collectibles	Dummy variable representing the categories, having the others as a reference: 1 = Collectibles	Dummy	Control	
Dummy: Time	Time dummy variable for the year 2013, with 2012 as the baseline: 1 = year 2013	Dummy	Control	

Note. Elaborated by the authors.

Panel data analysis and regression models

Panel data unify both cross-sectional (*i*) and time series (t) dimensions (Wooldridge, 2002). To review the study hypotheses and understand how product popularity (H1), number of transactions (H2), price adjustment (H3), and shipping time (H4) affect the levels of persistent dispersion (over time) of transaction prices, we initially tested the suitability of log-linear models against pooled OLS, fixed effects, and random effects estimators.

The use of log-linear models consists of applying a natural logarithm transformation, which is appropriate for measuring data that varies over time (Vargas et al., 2023). Models were not estimated with a first-difference estimator, since when T = 2, as in this study, there are no differences in the test statistics between the first-difference estimator and the fixed effects estimator (Baltagi, 2005).

The random effects estimator was used as the standard in our estimations, primarily based on theoretical reasons that indicate variation in the phenomenon of price dispersion over time (i.e, Ghose & Yao, 2011; Lach, 2002). We also considered the following: (1) the random effects model is an appropriate specification when randomly sampling N individuals from an extensive population (Baltagi, 2005). In this study, categories were randomly selected from a dataset with millions of observations (N → ∞) over time. As this is a short panel (N > T) with many cross-sectional observations, the random effects model is more efficient than the fixed effects model (Gujarati & Porter, 2011; Wooldridge, 2002); (2) it is assumed that the unobservable effects specific to each subcategory, for all *i* and *t*, are incorporated in the composite error term (*i*), are random and uncorrelated with the independent variables (Baltagi, 2005; De New & Zimmermann, 1994; Gujarati & Porter, 2011); (3) the results of the comparison tests between the pooled ordinary least squares (OLS) estimator, fixed effects and random effects. The random effects model was selected based on the test results (see Table 6), which met all the basic assumptions of regression models.

Thus, considering that each i represents a product subcategory and t represents time, CV and DifPercent are the dependent variables. The explanatory variables include Product_Popularity (Hypothesis 1), Transaction (Hypothesis 2), Price_Adjustment, Shipping_Time, and Buyers, which also vary between categories (*i*) and over time (*t*), along with the dummy variables Collectibles and Time.

The general form of random effects models is represented by the following specifications:

(1) $$\mathrm{Ln}(\mathrm{CV}_{it}) = \beta_0 + \beta_1 * \mathrm{Ln}(\mathrm{Product\_Popularity}_{it}) + \beta_2 * \mathrm{Ln}(\mathrm{Transaction}_{it}) + \beta_3 * \mathrm{Price\_Adjustment}_{it} + \beta_4 * \mathrm{Shipping\_Time}_{it} + \beta_5 * \mathrm{Buyers}_{it} + \delta_1 * \mathrm{Collectibles}_i + \delta_2 * \mathrm{Time}_t + \omega_{it}$$

(2) $$\mathrm{Ln}(\mathrm{DifPercent}_{it}) = \beta_0 + \beta_1 * \mathrm{Ln}(\mathrm{Product\_Popularity}_{it}) + \beta_2 * \mathrm{Ln}(\mathrm{Transaction}_{it}) + \beta_3 * \mathrm{Price\_Adjustment}_{it} + \beta_4 * \mathrm{Shipping\_Time}_{it} + \beta_5 * \mathrm{Buyers}_{it} + \delta_1 * \mathrm{Collectibles}_i + \delta_2 * \mathrm{Time}_t + \omega_{it}$$

where β_0 is the intercept term. β_1, β_2,..., β_5 are coefficients representing the individual effect of the independent variables on the dependent variables. δ_1 and δ_2 are the coefficients of the dummy variables. ω_{it} is the composite error term, which combines the specific error component of each category/cross-section (ε_i) and the idiosyncratic error (μ_{it}), i.e, $\omega_{it} = \varepsilon_i + \mu_{it}$ (Gujarati & Porter, 2011). The variable Time was introduced to control for trend effects on the models. We have also included the dummy variable Collectibles to capture possible unobservable effects at the level of product metacategories. These are important controls in panel data analysis that considers the passage of time, where averages of the effects of explanatory variables are constant.

MAIN RESULTS

Exploratory analysis

Table 3 shows the t-tests results, where test values refer to the comparison of means at the subcategory-year level for the years 2012 and 2013. Results show that the mean difference between posted prices and transaction prices is statistically significant ($p < 0.05$), with a smaller price dispersion for transaction prices, similar to Zhao et al. (2015) and Zhuang et al. (2018). Levene's test shows equal variances between the groups (defining 2012 and 2013 as factors). Table 4 shows descriptive analyses of variables separately for 2012 and 2013, respectively.

Table 3. Mean price dispersion at subcategory level.

	Subcategories 2012 and 2013			
	Mean price	Levene's test	CV	DifPercent
Posted price	262.68	F = 0.012 / p = 0.91	1.49	19.36
Transaction price	226.36	F = 0.006 / p = 0.93	1.46	18.10
t-statistic (H_0: dif = 0)	(p = 0.03)	—	(p = 0.17)	(p = 0.08)

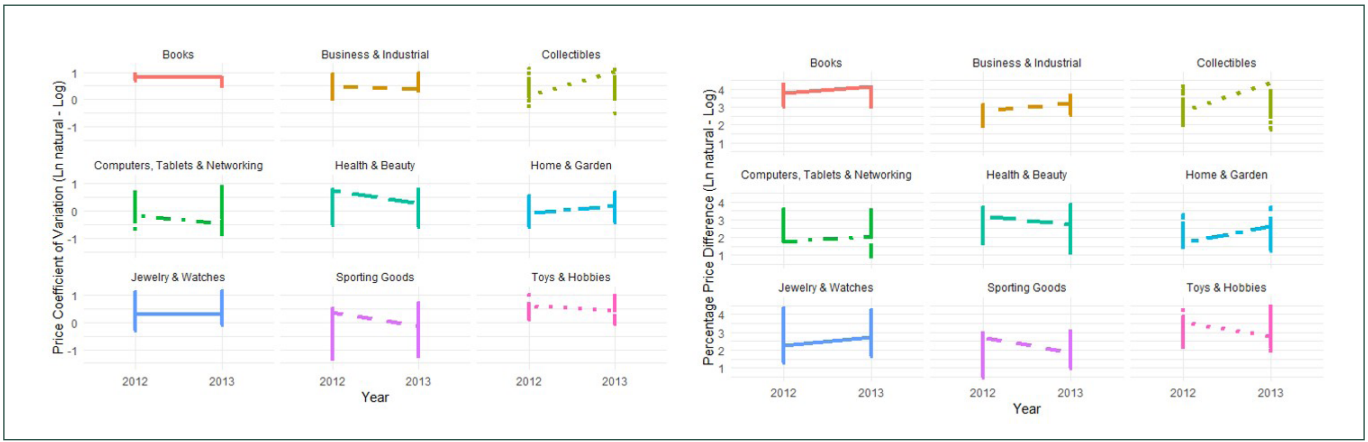
Note. Elaborated by the authors. CV: Price coefficient of variation.

Table 4. Descriptive analyses considering transaction prices (at the subcategory-year level).

Variables	Year 2012					Year 2013				
	n	Mean	SD	Min.	Max.	n	Mean	SD	Min.	Max.
Dependent										
CV	219	1.41	0.54	0.20	3.16	219	1.50	0.60	0.24	3.21
DifPercent	219	16.68	14.19	1.58	78.20	219	19.54	15.97	2.07	113.61
Explanatory										
Product popularity	219	1.63	1.07	0.19	10.03	219	1.78	1.11	0.25	9.82
Transaction	219	776.44	1349.78	168	15549	219	893.44	1383.75	178	15160
Prices adjustment	219	17.18	6.29	1.30	38.48	219	21.52	6.84	1.13	52.99
Shipping time	219	7.22	1.16	4.72	13.67	219	7.23	1.13	3.91	13.91
Buyers	219	635.01	1135.26	54	14033	219	730.75	1155.41	134	13739
Control										
Dummy: Collectibles	219	0.16	0.37	0	1	219	0.16	0.37	0	1
Dummy: Time	219	0	0000	0	0	219	1	0000	1	1

Note. Elaborated by the authors. Balanced panel: n = 219, T = 2, N = 438. SD: Standard deviation.

The 438 observations in the dataset encompass a broad spectrum of stacked transactions, amounting to a total of 365,704. Each subcategory involved a minimum of over 14,000 buyers in both 2012 and 2013. The popularity of products in each subcategory ranged from 0.19 to 10.03 in 2012 and from 0.25 to 9.82 in 2013. The percentage of price adjustment between products was 17.8% in 2012 versus 21.21% in 2013. The standard deviations of the number of transactions and the number of buyers point to the high heterogeneity of data, indicating high variability between the subcategories, which may be reflected in the levels of price dispersion over these years. Figure 2 provides evidence of the levels of price dispersion (mean) for each metacategory, where varied patterns in price behavior are observed.



Source: Developed by the authors. Panel A — Price coefficient of variation; Panel B — Percentage price difference

Figure 2. Transaction price dispersion at the metacategory-year level (2012-2013).

Table 5 presents the correlation matrix, showing the direction and strength of the linear association between price dispersion and the explanatory variables. Among the significant correlations identified for CV, Product Popularity ($r = -0.27$, $p < 0.001$) and Number of Transactions ($r = 0.28$, $p < 0.001$) stand out. For the DifPercent variable, the Number of Transactions shows a robust and positive linear correlation ($r = 0.59$, $p < 0.001$).

Table 5. Correlation matrix.

Variables	1	2	3	4	5	6	7	8
1. CV	—							
2. DifPercent	0.80***	—						
3. Product popularity	-0.27***	-0.14**	—					
4. Transaction	0.28***	0.59***	0.03	—				
5. Prices adjustment	0.19***	0.10*	0.02	0021	—			
6. Slower shipping time	0.17***	0.15**	0.03	0026	-0004	—		
7. Buyers	0.26***	0.55***	0.06	0.97***	0051	0022	——	
8. Dummy: Collectibles	0.18***	0.13**	0.06	-0000	-0049	0.15**	-0.054	—
9. Dummy: Time	0.06	0.10*	0.07	0043	0.31***	0001	0042	0.00

Note. Elaborated by the authors. Significance at: * $p < .05$, ** $p < .01$, *** $p < .001$.

Regression models for the transaction price dispersion drivers

To validate the estimates and results, specification tests were initially applied to select the ideal model for panel data, as shown in Table 6. The results for the three estimators are presented to reinforce the robustness of the set of explanatory variables included in the models. Thus, the tests applied confirm the suitability of the random effects model.

Table 6. Panel specification tests for transaction prices.

Estimator contrasts	I-III Models (CV)	IV-VI Models (DifPercent)
Pooled OLS vs. Fixed effects	F-test H_0: Pooled ($F = 6.91$, $p < 0.001$)	F-test H_0: Pooled ($F = 3.03$, $p < 0.001$)
Pooled OLS vs. Random effects	Breusch-Pagan LM test H_0: Pooled ($\chi^2 = 117.84$, $p > 0.001$)	Breusch-Pagan LM test H_0: Pooled ($\chi^2 = 52.68$, $p > 0.001$)
Fixed effects vs. Random effects	Hausman test H_0: Random Effects ($\chi^2 = 11.59$, $p = 0.71$)	Hausman test H_0: Random effects ($\chi^2 = 8.40$, $p = 0.2102$)

Note. Elaborated by the authors. The random effects estimator was determined to be the most suitable for the panel, based on the results of the tests conducted.

In log-linear models of the log-log type, coefficients are read as elasticities due to the linearity present in the natural logarithms of the Y and X variables (Vargas et al., 2023). In this instance, for each 1% increase in the explanatory variables, there is an impact of x% on the levels of transaction price dispersion, with the coefficient sign determining whether this impact is positive or negative. The log-lin relationship posits that the dependent variable exhibits exponential growth (or decay) in relation to the absolute variations in explanatory variables (Gujarati & Porter, 2011). Table 7 presents the results of the regression model estimations.

Table 7. Regression models for transaction price dispersion.

	Ln(CV)			Ln(DifPercent)		
	Model I pooled OLS	Model II fixed effects	Model III random effects	Model IV pooled OLS	Model V fixed effects	Model VI random effects
Interception	-1.268*** (0.226)		-1.016*** (0.249)	-1.400*** (0.345)		-1.310*** (0.395)
Ln (product popularity)	-0.211*** (0.028)	0046 (0115)	-0.189*** (0.036)	-0.278*** (0.043)	0208 (0247)	-0.263*** (0.052)
Ln (transaction)	0.144*** (0.033)	0.138* (0.071)	0.125*** (0.037)	0.502*** (0.051)	0.623*** (0.152)	0.512*** (0.059)
Prices adjustment	0.014*** (0.003)	0005 (0003)	0.010*** (0.002)	0.014*** (0.004)	0003 (0007)	0.011*** (0.004)
Shipping time	0.058*** (0.015)	0026 (0025)	0.047*** (0.016)	0.085*** (0.023)	-0013 (0053)	0.070*** (0.026)
Buyers	0.00002 (0.00002)	-0.0001 (0.0001)	0.00002 (0.00003)	0.00002 (0.00003)	-0.00004 (0.0002)	0.00002 (0.00004)
Dummy: Collectibles	0.228*** (0.048)		0.228*** (0.064)	0.301*** (0.073)		0.300*** (0.090)
Dummy: Time	-0014 (0037)	0008 (0026)	0005 (0021)	0033 (0056)	0017 (0056)	0041 (0042)
N	438	438	438	438	438	438
R^2	0.29	0078	0.20	0.45	0.19	0.37
Adjusted R^2	0.28	-0.89	0.19	0.44	-0.67	0.36
F-statistic	25.58***	2.99***	106.80***	49.92***	8.12***	256.99***

Note. Elaborated by the authors. Standard errors are indicated in brackets. The symbols ***, **, and * are used to denote significance at p < 0.001, p < 0.05, and p < 0.10, respectively. Unstandardized coefficients.

Random effects estimators were selected as the standard approach. As illustrated in Table 6, the variability of CV is explained by 20% of the variables included in the models, while DifPercent variability is explained by 37%, according to the coefficients of determination. The results suggest that as a product's popularity within a specific category on two-sided platforms increases, its price dispersion levels decrease. The coefficients were found to be statistically significant and negative, indicating a reduction in CV of -0.189% (β = -0.189, p < 0.001) and in DifPercent by -0.263% (β = -0.263, p < 0.001). These findings lend support to H1. The rationale underlying these reduction effects belongs to the notion that the popularity of the products is sustained by a broader audience, thereby signifying that a greater number of individuals have access to price distribution and a more substantial number of companies start marketing it.

Results also demonstrate a significant yet positive influence of the number of transactions on price dispersion, with 0.125% for CV (β = 0.125, p < 0.001) and 0.512% for DifPercent (β = 0.512, p < 0.001). These findings lend support to H2. The enhanced impact observed on DifPercent can be attributed to its heightened sensitivity to variables characterized by high standard deviations, thereby encompassing both minimum and maximum values. These results suggest that an increase in the number of product transactions in specific categories over time is associated with a significant impact on price dispersion metrics, consistent with Ghose and Yao (2011).

Likewise, a substantial and positive effect was identified for Price Adjustment on price dispersion, both for CV (β = 0.010, p < 0.001) and DifPercent (β = 0.011, p < 0.001). These findings lend support to H3. This finding aligns with the findings of previous research by demonstrating that: firstly, in the context of e-commerce, price adjustments are typically orders of magnitude smaller compared to conventional market fluctuations (Brynjolfsson & Smith, 2000); secondly, the impact of these adjustments is often more pronounced over extended periods (Bronnenberg et al., 2006). This is a marketing response that takes into account changes in the market in terms of demand and other sellers' prices (Chen et al., 2022).

Shipping time had a significant and positive effect on price dispersion, 4.7% for CV (β = 0.047, p < 0.001) and 7% for DifPercent (β = 0.070, p < 0.001). These findings lend support to H4. This suggests that products that take longer to deliver to customers have high levels of price dispersion. This may be related to the fact that two-sided platforms act as exchange intermediaries (Perren & Kozinets, 2018), connecting sellers and buyers with local and global identities. Geographical location has an effect on price dispersion (Zhuang et al., 2018) because it implies different seller-related costs and the time it takes to ship products.

The coefficients on the Collectibles control dummy are significant and positive, here suggesting that greater variability in the number of metacategories is associated with higher levels of price dispersion. This suggests that differences in the number of subcategories a metacategory has are potential sources of price dispersion on bilateral trading platforms. Similarly, the coefficients on the time control dummy variable are positive and significant, suggesting that price dispersion tends to increase over time. This indicates that buyers may have some difficulty in learning about price dispersion over time (Ghose & Yao, 2011). Table 8 shows a comparison between the random effects models of the posted price and the transaction price.

Table 8. Random effects models for posted price and for transaction price.

	Posted price		Transaction price	
	Model I Ln(CV)	Model II Ln(DifPercent)	Model III Ln(CV)	Model IV Ln(DifPercent)
Interception	-0.874*** (0.257)	-1.116*** (0.385)	-1.016*** (0.242)	-1.310*** (0.350)
Ln (product popularity)	-0.209*** (0.039)	-0.293*** (0.061)	-0.189*** (0.038)	-0.263*** (0.058)
Ln (transaction)	0.115*** (0.038)	0.493*** (0.059)	0.125*** (0.036)	0.512*** (0.056)
Adjustment	0.010*** (0.002)	0.012*** (0.004)	0.010*** (0.002)	0.011*** (0.003)
Shipping time	0.041** (0.016)	0.067** (0.027)	0.047*** (0.014)	0.070*** (0.022)
Buyers	0.00003 (0.00002)	0.00003 (0.00003)	0.00002 (0.00002)	0.00002 (0.00002)
Dummy: Collectibles	0.220*** (0.050)	0.276*** (0.074)	0.228*** (0.052)	0.300*** (0.073)
Dummy: Time	-0004 (0022)	0006 (0042)	0005 (0021)	0041 (0042)
N	438	438	438	438
R^2	0184	0354	0199	0374
Adjusted R^2	0171	0343	0186	0364
F-statistic	96.947***	235.634***	106.803***	256.997***

Note. Developed by the authors. Robust standard errors are indicated in brackets. The symbols ***, **, and * are used to denote significance at $p < 0.001$, $p < 0.05$, and $p < 0.10$, respectively. Unstandardized coefficients.

White's robust correction was included to deal with possible heteroscedasticities in the estimates of the posted price models, with the aim of holding the variance constant (Wooldridge, 2002). In short, results show that the transaction price models have coefficients with greater power to explain the variability in price dispersion.

DISCUSSION

This study examines how product popularity and other underlying mechanisms affect price dispersion on two-sided B2B and B2C marketing platforms. The dynamics of digital platforms go beyond commercial transactions and involve complex interactions that create value for different market actors and have significant implications for digital marketing (Hofacker et al., 2020). Relationships on digital platforms go beyond specific relational dynamics, as they aim at creating value for various market actors and generate significant implications for digital marketing (Hofacker et al., 2020). Results are consistent with the extension of literature that studies price dispersion, considering the multidimensional perspectives of supply and demand, as well as transaction prices.

The popularity of a product was found to be associated with a reduction in price dispersion. Managers and marketing professionals working on two-sided B2B and B2C platforms need to implement effective strategies to monitor product popularity levels to increase their visibility and attractiveness. This is particularly relevant in the current context, where online shopping is consolidating as a widely adopted habit, requiring more targeted and high-quality digital marketing campaigns (Desai & Vidyapeeth, 2019). As digital platforms are increasingly integrated into people's marketing plans and daily lives, it is imperative to invest in more efficient digital marketing campaigns, especially for those who prefer to shop in online stores (Desai & Vidyapeeth, 2019). In many situations, buyers tend to prefer products that have more reviews, even if well-reviewed products are of lower quality than less-reviewed ones (Powell et al., 2017). One way to increase popularity is to ensure that consumers rate their shopping experiences, filling in not only the overall rating but also the specific attributes of the product. This information strengthens consumers' trust in the product (Zhu & Zhang, 2010) and increases their likelihood of recommending it to other potential buyers (Lai et al., 2019).

The more information about the product's popularity is available, the more visits sellers receive (Tucker & Zhang, 2011), making the product more trustworthy (Zhu & Zhang, 2010) and more likely to be recommended to other target customers (Lai et al., 2019).

When selling popular products, sellers should also pay attention to the prices charged by competitors to achieve more convergent price levels. This convergence helps level the playing field, especially in markets where the range of options turns price into a critical attribute in consumer choice (Bown, 2007). Before making a purchase, consumers often research price and prestige levels, using product attributes, effectiveness, and features as comparison criteria (Sevilla & Townsend, 2016). Popular products tend to have low price dispersion due to greater market stability, resulting in sellers adjusting their prices to the market mean.

However, sellers look for ways to differentiate the prices of popular products in the market using a variety of pricing strategies, such as complementary packages and price discounts. For example, packages that combine complementary items, such as a smartphone with accessories, are a common strategy to increase perceived value and justify differentiated prices. Consumers' price sensitivity acts as a natural regulator, as it typically varies between selling a popular product on its own and selling a popular product with complementary packages (Jang & Chung, 2021). Sellers should balance competitive prices with the prestige of the store, preventing excessively high prices from damaging their reputation and driving away potential buyers (Sevilla & Townsend, 2016). Although digital platforms control consumer access (Bei & Gielens, 2022), the information they disseminate online about negative experiences can amplify this effect (Zhu & Zhang, 2010).

Results show that products with a high number of transactions have a high degree of price dispersion. This dispersion is strongly influenced by the discounts offered, which shape purchasing behavior over time (Bruno et al., 2012). For example, when discounts are higher than reference prices, consumers buy more; however, when discounts are lower, they prefer not to buy at that time because they do not see any benefits in the volume purchased at a high price (Krishna et al., 1991).

Price adjustments were found to have a positive effect on price dispersion. These findings highlight two important considerations for managers: (1) the costs involved and (2) the differences in the frequency of adjustments. Although it is easier and less costly to make price changes in e-commerce (Brynjolfsson & Smith, 2000), frequent, short-term adjustments tend to have a less significant impact on price dispersion than infrequent, larger changes, especially in the form of discounts (Bronnenberg et al., 2006). Price adjustments are also related to competitive dynamics. In markets with a large number of sellers, these adjustments, even if they occur frequently, tend to be less pronounced (Chen et al., 2022). On the demand side, price adjustments are greater in categories with larger market shares and price-sensitive buyers (Srinivasan et al., 2008). These considerations highlight the importance of a strategic and careful approach to price management in competitive environments such as two-sided platforms. To effectively adjust prices, managers should consider factors such as cost, competitiveness, and the impact on price variability.

Finally, results suggest that slower shipping methods have a positive impact on price dispersion. Buyers with a local identity may be less price-sensitive for products from both local and global firms (Gao et al., 2017). This implies that they choose to purchase products from distant geographic locations when prices are lower (Overby & Forman, 2015). This consumer behavior means that shipping time affects price dispersion, especially since the price of slower shipping may significantly vary between less expensive options. Managers should strive to improve their segmentation strategies for these different customer profiles, considering price sensitivity, as these consumers may be more valuable to companies (Jiang & Rosenbloom, 2005).

MANAGERIAL IMPLICATIONS

The term digital marketing is used as an umbrella to encompass various business processes that necessarily involve acquiring, retaining, and building loyalty among consumers, promoting brands, and increasing sales (Kannan & Li, 2017). In this reality, understanding the drivers of how individuals transact with products is important because it can guide the strategies of digital marketing and e-commerce companies operating in these markets. According to Cai and Choi (2023), although the Internet environment is efficient at conveying information, it is difficult for sellers in this space to control information and competitive processes between existing businesses, which ends up benefiting buyers (end consumers) more than sellers (e-commerce firms). This research tests a theoretical framework for price dispersion on two-sided platforms and contributes to digital marketing by providing knowledge about the drivers that influence price dispersion. The results address significant issues of managerial relevance from the perspective of firms practicing digital marketing (Kannan & Li, 2017).

For sellers and marketers working on two-sided platforms, this study brings managerial implications that significantly contribute to the optimization of pricing strategies, product promotion, and reputation management on digital platforms. The relevance of product popularity highlights the importance of developing strategies aimed at monitoring and increasing product visibility/exposure, encouraging positive feedback, and proactively managing online reputation. For example, the way products are displayed to consumers can affect their perceived experience, leading them to attach a higher value to the product and even affecting their perception of the store's prestige (Sevilla & Townsend, 2016). Popularity information from product reviews can also affect store sales (Tucker & Zhang, 2011) because, in some purchase situations, consumers tend to have a greater preference for products that are highly rated by other consumers (Powell et al., 2017). This is because the more popular a product is, the greater its appeal to consumers (Tucker & Zhang, 2011), as popularity is ultimately an indication of higher quality for certain products (Hanson & Putler, 1996).

Another important result is the relationship between the number of transactions and price dispersion. It suggests that transactional factors such as price, quality, and discount strategies can influence the consumer's purchase decision (Viswanathan et al., 2010). This is particularly important for managers of dominant brands who want to encourage high-volume purchases. Regarding price adjustments, understanding the dynamics between the short- and long-term guides managers in choosing effective strategies, considering elements such as cost, competitiveness, and the impact of price fluctuations. The suggestion of making strategic adjustments based on product attributes, such as setting higher prices for high-quality products and lower prices for lower quality complementary products (Jang & Chung, 2021), highlights the importance of a differentiated and more assertive approach to pricing on two-sided platforms.
Results also address the use of the price discount strategy. The focus of this mixed strategy should be based on the use of intermittent and unexpected offers so that firms avoid predictable patterns (Lindgren et al., 2020) and maximize the positive impact on purchase decisions. This strategy allows companies to maintain their profit margins and avoid buying behaviors conditioned by discount periods.

LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

While this study makes important theoretical and managerial contributions, it is not free of limitations. First, the analysis used panel data for several product categories covering only a two-year period (2012-2013) limiting a broader longitudinal investigation. Although two-sided platforms retain their structure as intermediaries or hubs, complementary studies with more recent data may be needed to capture the impact of technological and behavioral changes on e-commerce dynamics and digital marketing strategies. In addition, the period analyzed, prior to the COVID-19 pandemic, represents a limitation in terms of capturing recent impacts that have deeply changed consumer behavior and the adoption of digital platforms. Although the basic relationships examined remain relevant, such as the relationship between popularity and price dispersion, further studies could incorporate post-pandemic data to see how these changes have influenced the dynamics identified in this work.

Further research could also capitalize samples with longer time periods, explore scenarios with fixed effects estimators and generalized least squares, and extend these analyses with mitigated heteroscedasticity. A more complex analytical approach, such as the use of multilevel models or machine learning techniques, may be used to examine patterns in hierarchical data or in large datasets related to transactions and platforms. In addition, authors can enrich their approaches by incorporating multiple methods, triangulating secondary and primary data to reflect buyers' perceptions of the actual possibility of purchasing popular products, especially for those who are more price-sensitive. This approach could further validate the findings of this study and deepen the understanding of the relationship between price dispersion and product popularity.

The inability to determine the number of popular products added to the wish list that were purchased is a limitation. Understanding this proportion would be crucial for highlighting to managers the importance of managing reviews and comments more efficiently, providing valuable insights for improving marketing strategies. Future studies could extend the analysis to second-hand products, given that this research is limited to new products. For example, the authors could explore how the willingness of sellers to accept lower bids might affect price dispersion in this specific context. Second-hand products often imply less rigidity in initial prices (Backus et al., 2020).

Although this study used the frequency with which a product was added to the wish list as a measure of popularity, it could not determine whether this consumer decision considered an adequate level of valence information, such as positive or negative feedback (Jang & Chung, 2021). In addition, the study did not review which specific content, such as functional or emotional aspects of the product, was used as criteria in the purchase decision. This information is essential for developing marketing strategies that balance popularity, product attributes, and pricing practices.

Although this study showed that price dispersion is correlated with transaction volume, the review was limited to identifying patterns and temporal associations without establishing a direct causal relationship between these variables. It is important to note that while literature on marketing extensively documents how promotions and price adjustments affect dispersion, this study offers an innovative approach by exploring the phenomenon in the specific context of two-sided platforms, highlighting transaction volume as a factor associated with higher levels of price dispersion. Two-sided platforms, such as eBay, have unique attributes that distinguish them from traditional price promotion models. For example, direct negotiations between buyers and sellers can result in transaction prices that differ significantly from the prices originally posted. Depending on the concessions made during negotiations, the volume of transactions can vary significantly (Backus et al., 2020).

Therefore, future research is needed to establish causality based on the observed associations, for example, using experimental designs. Researchers could also extend the findings of this study to examine how external factors, such as economic crises or cultural changes, affect the relationship between popularity and price dispersion. In addition, a comparative analysis between different two-sided platforms would be enriching to assess the generalizability of results and to identify specific attributes of each business model operating in those ecosystems.

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