Online Price Dispersion Revisited: How Do Transaction Prices Differ from Listing Prices?

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ABSTRACT: Price dispersion of a homogeneous product reflects market efficiency and has significant implications on sellers' pricing strategies. Two different perspectives, the supply and demand perspectives, can be adopted to examine this phenomenon. The former focuses on listing prices posted by sellers, and the latter uses transaction prices that consumers pay to obtain the product. However, no prior research has systematically compared both perspectives, and it is unclear whether different

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perspectives will generate different insights. Using a unique data set collected from an online market, we find that the dispersion of listing prices is three times higher than the dispersion of transaction prices. More interestingly, the drivers of price dispersion differ significantly between listing and transaction data. The dispersion of listing prices reflects sellers' perception of market environment and their pricing strategies, and it may not fully capture consumer behavior manifested through the variation of transaction prices. Our study indicates that the difference in perspectives taken on the online prices yields different results as to their dispersion.

KEY WORDS AND PHRASES: listing prices, online markets, online prices, price dispersion, transaction prices.

Classical microeconomic theory predicts the "law of one price" for homogeneous goods in friction-free markets, where firm competition is perfect and consumer search cost is zero. However, extensive empirical studies in the past several decades have challenged the existence of friction-free markets and the "law of one price." It has been found that price dispersion is ubiquitous and persistent across various homogeneous product markets, such as books, gasoline, automobiles, consumer electronics, and airlines [4, 7, 12, 16, 20, 43, 57]. Price dispersion stems from many factors, including seller heterogeneity (e.g., varying service qualities, reputation), consumer heterogeneity (e.g., brand loyalty), search costs, market structure, and bounded rationality [2, 5, 11, 12, 37, 43]. Even in electronic markets where information transparency is largely improved and search costs are significantly reduced, the dispersion of prices for a homogeneous product is still a common phenomenon [27, 28, 51, 57, 60].

Extensive literature has examined price dispersion theoretically and empirically in order to gain insights into market conditions resulting in potential price discrimination strategies [4, 10]. Two different perspectives, the supply and demand perspectives, have been used to examine this phenomenon [28]. The former focuses on listing prices posted by the sellers, and the latter uses transaction prices that consumers pay to obtain the product. However, very limited research has adopted both perspectives in one study, so it is unclear whether these two perspectives will generate consistent insights. In other words, *does the dispersion of listing prices differ from that of transaction prices and how*?

In an efficient market with fully informed consumers and rational sellers, both listing and transaction prices will converge to the marginal cost of the product [8, 10]. Thus, there is no need to differentiate between the supply and demand perspectives. However, markets are rarely completely efficient, and the variation of listing prices is not always the same as the variation of transaction prices. For example, buyers and sellers often have asymmetric information [47, 69], or they may be bounded rational. When setting their prices, some sellers may not have rational expectation of consumers' willingness to pay, and thus a proportion of listing prices may never be realized eventually because they are not competitive in the market. Anecdotal evidence also indicates that the dispersion of transactions prices differs from the dispersion of listing prices. Ghose and Yao [27] find that the difference between listing prices of a pencil sharpener can be as great as $12.19, whereas its transaction prices differ only a few cents in their data set. Similarly, in our case, the listing prices for the Coach handbag style Kristin Leather Cross-body, range from ¥780 to ¥1,667 in an online microbusiness market, but its transaction prices range only from ¥898 to ¥988.

Due to these potential differences, it is important to investigate and compare the dispersion of listing prices and the dispersion of transaction prices in order to obtain a complete picture of the market. The dispersion of listing prices reflects sellers' pricing strategies when facing competition in the market, whereas the dispersion of transaction prices characterizes consumers' reaction to alternative offerings in the market [51]. In addition, exploring the differences can shed light on information asymmetry and interactions between the supply and demand sides in a market [26, 49].

Prior studies have not closely investigated the differences between the dispersion of listing prices and the dispersion of transaction prices. Theoretical work typically focuses on the equilibrium price or market clearing price where the quantity supplied equals the quantity demanded [6, 7]. Meanwhile, most empirical research largely employs listing prices to explore price dispersion [16, 39, 51, 64], primarily because the listing price data are relatively easier to acquire than the transaction price data. Two recent studies use transaction prices to understand price dispersion in online markets [13, 27], but neither of them has offered a one-to-one comparison of listing and transaction prices. Ghose and Yao [27] find that the dispersion of transaction prices in the online Federal Supply Service (FSS) market designed for U.S. government procurement can be as low as 0.22 percent, suggesting that the "law of one price" is possible. Price dispersion in Ghose and Yao [27] is substantially lower than that reported in prior literature. However, unlike our study, they do not have listing price data in the same market. Thus it is unclear whether such a low price dispersion level stems from using transaction prices alone or from features specific to the FSS market. The study by Chellappa, Sin, and Siddarth [13] is among the first to compare listing prices with transaction prices in the domestic U.S. airline market. In contrast to Ghose and Yao [27], they find that transaction prices are more dispersed than listing prices. However, their comparison is not conclusive because the records in their transaction prices data set do not perfectly match those in their listing prices data set. Specifically, their listing prices data set comes purely from the online market, while the transaction prices data set mixes both online and offline transactions. It is well known that consumer behavior can vary significantly across online and offline channels [19]. In addition, a few explanatory variables are only available in the listing prices data set, and as a result the impacts of these variables on the dispersion of transaction prices cannot be fully investigated. Our study differs from Chellappa, Sin, and Siddarth [13], in that our data set includes both listing and transaction prices for homogeneous goods from the same online market, and we compare the impacts of the same set of antecedents of price dispersion.

Our study contributes to the literature in the following ways. First, as one of the first studies to systematically compare the levels of price dispersion between the supply and demand perspectives, our research provides quantitative evidence that listing prices are more dispersed than transaction prices. Specifically, in our research context, the dispersion of listing prices is three times higher than the dispersion of transaction prices. Second, we propose and empirically validate that the drivers of price dispersion also differ between the two sides of the market. Sellers' perception and reaction to the market environment determine the dispersion of listing prices, whereas consumer search preferences and shopping behavior drive the variation of transaction prices [45]. Our results demonstrate interesting asymmetries in the market. It is likely that some sellers do not fully understand consumers' behavior, or they choose satisficing rather than optimal pricing strategies. Consequently, sellers' pricing heterogeneity does not perfectly reflect consumers' purchase decision heterogeneity. Our study raises the caution that the extent of price dispersion and the relationship between economic primitives and price dispersion depend on the perspective taken in individual studies. Third, we also expand the scope of product categories examined in price dispersion research. Prior studies focus mainly on product categories such as airline tickets, books, CDs, and electronics [16, 27, 39, 48, 57]. We study luxury goods, a category that has not been examined in depth in prior literature. Price dispersion research is context dependent; as Baye, Morgan, and Scholten indicate, "there is not a one-size-fits-all model of equilibrium price dispersion" [7, p. 359]. Prior studies often differ in their findings on how various drivers influence price dispersion, and the applicability of those findings is subject to different market environments [16, 48]. Thus, extending empirical examination of price dispersion into a new setting, the luxury goods traded in an online market, may be particularly valuable.

Theory and Hypotheses

The literature on economics, marketing, and information systems (IS) has examined various factors leading to the dispersion of prices in both offline and online markets. In general, drivers of price dispersion come from three levels—market, retailer, and product [10, 51, 66]. Our model includes all key market characteristics summarized by Pan, Ratchford, and Shankar: "item price level, number of competitors in market, product popularity in market" [51, p. 128]. We also consider retailer heterogeneity and product characteristics.

To answer our research question, we first examine whether the level of price dispersion differs between the supply and demand sides of the market. Then to better understand the difference between listing and transaction prices, we explore whether the key drivers of price dispersion and their impacts vary between the two sides of the market.

The Dispersion of Listing Prices versus the Dispersion of Transaction Prices

We study an online market where multiple sellers offer a homogeneous product. These sellers differ in terms of popularity and reputation established in the market

[10]. They are owner-managers of microbusinesses, who are bounded rational and tend to rely on informal information to make satisfying rather than profit-maximizing decisions [29]. As a result, for a given product, we have observed considerable variation among listing prices offered by these sellers.

Similar to Ghose and Yao [27], we hypothesize that the dispersion of transaction prices is lower than the dispersion of listing prices in such an online market. A transaction price occurs when a buyer agrees to buy a product from a particular seller. The process of matching buyers and sellers indicates that transaction prices usually represent only a subset of listing prices. In particular, due to the existence of less expensive alternatives, buyers are less likely to buy at listing prices at the high end. In addition, listing prices at the low end may look suspicious or not be honored (i.e., sellers' bait-and-switch tricks) [51]. Therefore, we expect that the dispersion of listing prices serves as "an upper bound" on the dispersion of transaction prices [27, p. 2].

Hypothesis 1: The dispersion of transaction prices is lower than the dispersion of listing prices.

The Price Level

Product price levels have long been considered an important source of price dispersion [10], and Stigler [61] suggests that expensive items would have lower price dispersion than cheap items. According to the search-theoretic models of price dispersion, varying search costs encountered by consumers split up the market and lead to price discrimination [54]. More search activities may reduce information asymmetry between sellers and buyers, leave fewer uninformed consumers in the market, and result in less price fluctuation. The extent of information search engaged by consumers is determined by both their ability to search and their motivation to search [55]. For more expensive products, consumers are motivated to conduct more intensive search. Price can be viewed as a proxy of consumer involvement [50], and the enduring involvement and shopping enthusiasm associated with more expensive products encourage consumers to increase their information search activities [55]. In addition, consumers are more cautious toward items that account for a larger share of their budgets, and they pursue higher potential savings from these expensive items [40, 52, 71]. Increased search from highly involved consumers can pressure sellers to be vigilant and set prices toward a competitive level. Some empirical evidence confirms this conjecture. For instance, Stigler [61] finds that the expensive product, automobiles, has lower price dispersion than the less expensive product, anthracite coal. In another study, Eckard [24] traces price dispersion for staple products from 1901 to 2001. He finds that price dispersion increases over time as the proportion of household budgets that these products account for decreases from 1901 to 2001. Therefore, we hypothesize:

Hypothesis 2a: The level of price dispersion is negatively associated with the price level of a product.

More intensive search associated with a more expensive product is expected to reduce its price dispersion, and this effect may be stronger on the demand side than on the supply side. Buyers, rather than sellers, directly face costs in searching information prior to purchase. Compared with sellers, buyers have stronger incentives to engage in intensive search activities in order to reduce prices that they pay in a transaction. Buyers rely on others' transaction records to justify their own purchase, leading to converging transaction prices. On the supply side, classic economic theory predicts that increased search activities intensify competition and lower margins for sellers [42]. However, in online markets where the majority sellers are owner-managers of microbusinesses, sellers are often bounded rational or perform satisficing instead of profit-maximizing behavior [30]. Some sellers possibly do not recognize that buyers would search more for more expensive products. Furthermore, cost components, such as sourcing costs and inventory costs, can be different among sellers. Bounded rationality and varying costs may limit some sellers' ability to offer more converging prices for more expensive products. So we propose the following hypothesis:

> *Hypothesis 2b: The negative impact of the price level on price dispersion is stronger for transaction prices than for listing prices.*

The Number of Competitors

The extent of price dispersion also depends on the competitive environment, which can be measured by the number of sellers or competitors offering a homogeneous good in the same market. Interestingly, the theoretical prediction and empirical evidence of the relationship between the number of sellers and price dispersion are mixed [5]—Cohen [18] concludes that the number of competitors is a "double-edged sword" in a market function.

Based on prior literature, we summarize there are two effects that can potentially influence the relationship between the number of sellers and the extent of price dispersion. The first effect is the competition effect, which suggests that the dispersion of prices drops with increased competition. Classic economic theory suggests that market competition will be intensified when there are more sellers offering the same product [62]. In a competitive market, consumers have multiple choices of a product, and sellers are pressed to set their prices competitively in order to compete with other sellers. Thus, more densely populated markets may demonstrate less price dispersion. For instance, Barron, Taylor, and Umbeck [5] find that less price dispersion is associated with a higher number of gasoline stations in the same geographical area. Pan, Ratchford, and Shankar [50] show that the number of competitors is negatively associated with price dispersion on a price comparison website for books, CDs, DVDs, computer software and hardware, and also consumer electronics.

The second effect is the search cost effect—increasing the number of sellers can boost price dispersion due to higher search costs [6, 61]. Consumers incur a higher search cost when there are more sellers in the market. They may be informationoverloaded or confused with a larger number of alternatives. Although search costs have been reduced significantly in online markets, they have not been completely eliminated yet [56]. For instance, the lowest price can be easily identified via various search tools provided by online markets, but price is not the only attribute that consumers care about [71]. Many buyers still delve deeply into individual sellers' profiles and their prior transaction records in order to compare and select the seller from whom they are willing to purchase the product. Intensive search is particularly important in the context of online microbusiness markets, where sellers are unbranded and unknown to consumers. Empirically, data from the U.S. airline industry suggest a positive relationship between price dispersion and the number of competitors. Several studies show that prices are more dispersed when market concentration, which is measured by the number of airlines offering services on the same route, increases [9, 13]. However, conflicting results also exist in the same airline industry. Martin and Koo [44] find that the competition intensity does not significantly affect the variation of the airfares over time. Such mixed findings suggest that the relationship between the number of competitors and price dispersion is complicated and warrants further exploration.

We suggest that the competition effect is more relevant to sellers, whereas the search cost effect is more applicable to buyers. Sellers directly face market competitive pressures. Compared with buyers, they are more sensitive to the existence and actions of competing sellers. When there are more competitors, sellers will find it more difficult to maintain a price that is higher than that of other sellers [5]. By contrast, buyers, rather than sellers, directly bear search costs in the shopping process. When the number of sellers in the market increases, some consumers may not have enough capacity to exhaustively search all alternative offerings. The result is that some consumers are less informed and likely to choose a seller whose price is not among the lowest in the market [11]. Therefore, we hypothesize:

Hypothesis 3a: The number of competitors is negatively associated with the dispersion of listing prices.

Hypothesis 3b: The number of competitors is positively associated with the dispersion of transaction prices.

Seller Reputation Heterogeneity

Seller heterogeneity is a key driver of price variation of homogeneous products. The reason is that sellers can profit by charging a price premium via differentiated service offerings, privacy protection, and trust signaling [12, 16, 20, 37, 43, 54]. In online markets, consumers potentially face higher transaction risks, such as scamming and fraudulent business transactions, than they do in face-to-face transactions [49]. It is difficult to verify the authenticity or quality of the listed products prior to online purchases. To reduce such risks, consumers evaluate the trustworthiness of the sellers in order to ensure a satisfying shopping experience [14, 50]. Typically, sellers have various strategies to signal their trustworthiness, including improving brand awareness, advertising, and building a reputation [4, 12]. In our research context, sellers are microbusiness owners who have rarely established well-known names, and they often face low consumer awareness and loyalty due to lack of branding. They also do not have much advertising budget to signal their trustworthiness. Therefore, reputation building is an important viable strategy used by sellers to manifest trust [10]. The seller reputation mechanism is also important in the context of shopping for luxury goods in an online market. Average consumers rarely buy luxury products repetitively or frequently, so most of them have limited transaction history or personal experience in interacting with the sellers. Consumers thus heavily rely on sellers' reputation to make their purchase decisions. Therefore, we focus on seller reputation heterogeneity in this research.

The marketing literature suggests that reputation impacts consumers' price perceptions [21]. Consumers are willing to pay price premiums for trustworthy sellers in order to minimize potential exchange risks [50]. As a result, sellers' reputation becomes their competitive advantage and enables them to price higher in the market. Reputation building also has the property of network externalities, as "more customers create a stronger signal of trust and strong signals of trust may lead to more customers" [10, p. 579]. Reputable sellers may not only enjoy price premiums from higher trustworthiness perceived by consumers but also benefit from a larger potential market size. Therefore, the larger the differences among sellers' reputation, the greater price dispersion is, and we hypothesize:

> *Hypothesis 4a: Heterogeneity in sellers' reputation is positively associated with the level of price dispersion.*

Seller reputation, as a viable tool for differentiation in an online market, can be a source of price premiums and a cause of price dispersion. However, we expect that the impact of seller reputation heterogeneity on price dispersion will be weaker for transaction prices than for listing prices. On one hand, less reputable sellers may suffer from the loss aversion effect [36]. Loss aversion describes people's tendency to strongly prefer the avoidance of losses to the acquisition of gains. In our context, buyers are highly involved and are not attached to the brand of sellers, and are thus more influenced by negative information than by equally extreme positive information [1]. These buyers might avoid conducting potentially risky transactions with less reputable sellers, even though the latter charge lower listing prices. On the other hand, highly reputable sellers may face consumers' diminishing marginal utility of reputation [46]. Studies show that sellers receive little or no reward after their reputation goes beyond a certain threshold [41], and high listing prices offered by highly reputable sellers can be unattractive to potential buyers. Consequently, listing price variation caused by reputation heterogeneity among sellers may not manifest on the demand side due to unrealized transactions. This leads to our following hypothesis:

> *Hypothesis 4b: The positive impact of seller reputation heterogeneity on price dispersion is weaker for transaction prices than for listing prices.*

Empirical Context, Data, and Descriptive Analyses

Product Selection

We chose luxury handbags as the focal product category in this study for several reasons. First, the luxury good market is an important but understudied economic sector. It has experienced spectacular growth since the 1980s as middle-market consumers have traded up [59], but related research is still limited compared with nonluxury counterparts [23, 67]. Specifically, luxury goods have not been systematically investigated in price dispersion research. Prior studies on price dispersion have examined product categories such as books, office supplies, electronics, and airfares [e.g., 13, 16, 27]. However, findings of price dispersion studies are often sensitive to product types [68]. Thus, exploring luxury handbags can help us to gain additional insights. Second, branded handbags ensure standardization. No matter how individual sellers in online markets source their luxury designer handbags, the products are originally distributed by the same brand owners and are of the same quality. Therefore, it is reasonable to assume product homogeneity in our research context. Third, luxury handbags are high-involvement products. Luxury goods satisfy not only consumers' utilitarian performance but also their sensory pleasure and social status signaling [67]. The combination of luxury goods and expensive prices causes consumers to be highly involved in the shopping process of luxury goods, and consumer involvement matters in the mechanisms causing price dispersion [17]. Last but not least, some general confusion exists between the supply and demand sides of the luxury good market [67]. It is thus desirable for us to study the differences in price dispersion between the two sides of the luxury good market.

We examine the luxury good market in China, which is predicted to account for about 20 percent of global luxury sales in 2015 [3]. We selected both the most prestigious luxury brand, Louis Vuitton (LV), and the "affordable luxury" brand, Coach. LV is often top ranked among the most powerful luxury brands whereas Coach is renowned for introducing the "accessible luxury" to the masses [32]. Both LV and Coach are popular luxury brands among Asian consumers [31, 38]. LV products were reported as the most desired brands in China in 2011, according to research by Bain and Co. [70]. And Coach was the third best-selling brand in the Chinese market with a turnover of $300 million in the first half of 2012 and annualized sales growth of 60 percent [53]. Including both brands increases the external generalizability of our results.

The Electronic Market

We collected data from Taobao Marketplace, the largest Internet retail and trading website in China. It services more than 800 million product listings and more than 500 million registered users as of June 2012. The combined gross merchandise volume of Taobao Marketplace and Tmall.com exceeded RMB1 trillion, accounting for approximately 90 percent of China's e-commerce market (http://news.alibaba.com/specials/aboutalibaba/aligroup/index.html).[1] Taobao Marketplace provides microbusiness owners with a platform to run online retail stores and post their products for sale. Taobao Marketplace has a number of sellers listing luxury designer handbags such as LV and Coach. For a specific luxury handbag style, the number of sellers ranges from a couple to more than 100. In addition to typical listing information, Taobao also posts the transaction records for a listed product in the past thirty days. The rich information available on Taobao.com enables us to investigate both the listing and transaction activities in the same online market.

Data Collection

Our data collection includes two steps. First, we collected the Coach and LV handbag information, such as style number, official price, size, material (leather/no leather), and being a new arrival or not, from the official websites (www.coach.com and www.louisvuitton.fr). The data collection from the official channels was conducted twice, first in April 2011 and then in September 2011, so that new products released for the fall/winter collection were incorporated. The second step of data collection was performed once per week from May 30, 2011, to January 23, 2012 (about thirty-four weeks). We developed a web-based spider using multiple languages such as python, wget, and perl to automatically retrieve all listing pages of LV and Coach handbags in the Taobao Marketplace based on the Coach and LV style numbers collected from the official channels in the first step (Figures 1a and 1b).We then used a parser that we developed using Bash shell script to extract the listing and transaction data such as listing prices, numbers of listing pages being added to wish lists, seller location information, seller reputation scores, transaction history, and so on, from each listing page.

Data Description

Our data set consists of Coach and LV handbags' style information, and Taobao listing and transaction records from June 2011 to January 2012. The unit of analysis, i, is a handbag style (e.g., LV M41528, Speedy 25 Monogram Canvas). We study the dispersion of listing prices among all sellers offering the same handbag style as well as the dispersion of transaction prices of the same style. Because transactions are sparse (some handbag styles have no transaction in a given week during the data collection period), the temporal unit t used in this analysis is "month."

We use seller location in the e-commerce market to control for the possibility of counterfeit products. The data set used in the analysis includes only overseas e-commerce sellers, whose locations are not listed as in Mainland China. In Taobao Marketplace, these overseas sellers provide DaiGou services, that is, they sell branded products purchased from overseas markets to consumers in China. Luxury handbags are priced higher in China than in origin countries due to heavy tariffs, and

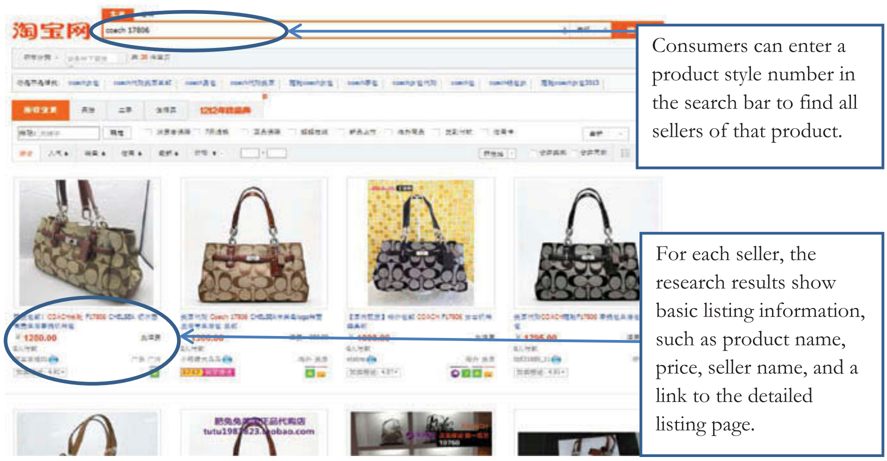

Figure 1a. Taobao product search page

Figure 1b. An example of a seller's listing page on Taobao.com

DaiGou sellers can arbitrage by sourcing handbags from the official channels in their local markets and selling them back to China via Taobao. Table 1 presents the descriptive statistics for our data.

We use two widely adopted metrics, percentage difference (*PD*) and coefficient of variation (*CV*), to quantify *price dispersion* [37]. *PD* is calculated as the difference between the highest (listing) price (*LP*) and the lowest (transaction) price (*TP*), divided by the mean price for a handbag style across different sellers or buyers. *CV* is calculated as the ratio of standard deviation of the prices to the mean price for a handbag style across different sellers or buyers. Both measures allow us to compare the dispersion of one data series to another even if the means are different. For both listing and transaction prices data sets, we run the analysis using *PD* or *CV,* respectively, as the dependent variable to check the robustness of the results. We

Table 1. Summary Statistics

Variables	Description	Brand	Obs.	Mean	S.D.	Min.	Max.
LP	Listing prices posted by sellers	Coach	50,436	2,584.68	1,430.73	325	97,450
		LV	61,889	8,077.48	21,794.00	1,619.5	788,912
PDLP	(Highest listing price–lowest listing price)/Mean	Coach	1,576	0.63	0.50	0	7.51
(*DISPERSION*)	listing price per handbag style	LV	1,769	1.87	6.85	0	77.69
CVLP	Standard deviation of listing price/Mean listing price	Coach	1,544	0.17	0.10	0.0039	1.57
(*DISPERSION*)	per handbag style	LV	1,643	0.33	0.74	0	6.07
TP	Transaction prices recorded by Taobao	Coach	13,685	2,013.33	739.06	280	12,390.27
		LV	14,179	6,483.94	3,031.80	2,000	81,000
PDTP	(Highest transaction price–lowest transaction	Coach	651	0.17	0.20	0	1.06
(*DISPERSION*)	price)/Mean transaction price per handbag style	LV	492	0.26	0.41	0	4.04
CVTP	Standard deviation of transaction price/Mean	Coach	481	0.085	0.067	0	0.33
(*DISPERSION*)	transaction price per handbag style	LV	373	0.13	0.15	0	1.15
PRICE	Official price in the origin country (in RMB)	Coach	1,576	2,245.00	1,235.84	365.97	9,064.44
		LV	1,848	9,732.67	5,826.90	1,449.23	30,604.2
POPULARITY	Average count of a handbag style being added to	Coach	1,576	2,245.01	1,235.84	365.97	9,064.44
	consumers' wish lists per handbag style	LV	1,769	2.14	3.50	0	47
SELLER	Number of sellers for a style	Coach	1,576	32.37	37.45	0	305
		LV	1,848	33.48	41.41	0	319
SR	Seller ratings: seller reputation scores	Coach	48,298	3,408.84	8,877.33	0	136,763
		LV	59,797	2,811.55	10,247.73	0	166,135
PDSR	(Highest seller rating–lowest seller rating)/Mean	Coach	1,563	7.41	5.29	0	46.01
(*DISPERSIONSR*)	seller rating per handbag style	LV	1,765	9.32	9.89	0	76.53
CVSR	Standard deviation of seller ratings/Mean seller	Coach	1,543	1.77	0.59	0.17	4.50
(*DISPERSIONSR*)	rating per handbag style	LV	1,640	2.01	0.96	0	6.03

STYLEAGE	Style age: number of months elapsed since a handbag style's data were first collected	Coach	1,576	4.07	2.25	1	8
		LV	1,848	4.07	2.25	1	8
NEWARRIVAL	Whether a handbag style is a new arrival (1 if new arrival and 0 otherwise)	Coach	1,576	0.26	0.44	0	1
		LV	1,848	0.15	0.36	0	1
AVAILABILITY	Whether a handbag style is available in official channels in China (1 if available and 0 otherwise)	Coach	1,576	0.23	0.42	0	1
		LV	1,848	0.49	0.50	0	1
ST	Seller tenure: number of days elapsed since the store was launched	Coach	48,302	941.62	926.36	0	40,730
		LV	59,807	761.27	2,126.32	0	40,912
PDST (*DISPERSIONST*)	(Highest seller tenure–lowest seller tenure)/Mean seller tenure per handbag style	Coach	1,564	2.92	4.67	0	43.55
		LV	1,769	5.55	9.99	0	50.89
CVST (*DISPERSIONST*)	Standard deviation of seller tenure/Mean seller tenure per handbag style	Coach	1,544	0.80	0.37	0.13	3.53
		LV	1,643	1.10	0.95	0	4.48
TQ	Transaction quantity: number of handbags sold by a seller in the past month	Coach	48,302	0.118	1.70	0	97
		LV	59,807	0.0829	0.906	0	99
PDTQ (*DISPERSIONTQ*)	(Highest transaction quantity–lowest transaction quantity)/Mean transaction quantity per handbag style	Coach	1,543	0.40	1.22	0	15.50
		LV	1,640	0.23	0.75	0	11.97
CVTQ (*DISPERSIONTQ*)	Standard deviation of transaction quantity /Mean transaction quantity per handbag style	Coach	1,543	0.15	0.36	0	3.29
		LV	1,640	0.097	0.28	0	2.96

Notes: When there is only one observation for a handbag style, the values of *PD* and *CV* are zero and null, respectively. We thus have fewer observations for the *CV* values than the *PD* values for some variables.

therefore have four dependent variables—*PD* of listing prices (*PDLP*), *CV* of listing prices (*CVLP*), *PD* of transaction prices (*PDTP*), and *CV* of transaction prices (*CVTP*).

The variable *PRICE* is defined as a handbag style's price in the origin country. It approximates individual sellers' sourcing prices and is an important benchmark they use to set prices on Taobao. Specifically, we use Coach's prices in the United States and LV's prices in France in the analysis. The variable *SELLER* represents *the number of sellers* for a handbag style, which is measured by the number of listings for a handbag style in the market. On Taobao, a seller creates a listing page for a handbag style that s/he sells, so the number of listings approximates the number of sellers. The variable *DISPERSIONSR* represents *seller reputation heterogeneity*, which is measured by the dispersion of seller ratings. We adopted the reputation scores provided by Taobao. Taobao runs a feedback system that allows a buyer to rate the seller as positive, neutral, or negative after each transaction. Taobao assigns values, 1, 0, –1, to positive, neutral, and negative feedback, respectively, and calculates the rating of a seller by totaling the values of buyer feedback for that seller. Both *PD* and *CV* are calculated for seller ratings so in the analysis we keep the measures of seller reputation heterogeneity consistent with that of the dependent variable, that is, we use *PD* (or *CV*) of seller reputation when *PD* (or *CV*) is used for price dispersion.

We include several variables to control product heterogeneity and relevant market features. Popular products, compared with niche products, tend to draw more attention from consumers and reinforce their own sales [25, 65]. Such high awareness among consumers can help ease consumers' search efforts, leading to lower price dispersion. Therefore, we include a variable, *POPULARITY,* which is measured by the counts of a handbag style being added to consumers' wish lists. If a consumer is interested in a particular handbag style from a seller, s/he can add the listing page to a personal wish list to trace the item later. Thus the number of a handbag style being added to wish lists reflects the potential market interest for it. Because the cumulative wish-list count of a handbag style is nondecreasing in the number of sellers, we normalize the wish-list count by averaging the counts by sellers. We include a *BRAND* variable with 1 representing LV and 0 representing Coach. Consumers may enthuse about new arrivals and this can impact sellers' pricing strategies. We therefore use a dichotomous variable, *NEWARRIVAL,* which equals 1 if the handbag is newly released and 0 otherwise. The market may shrink as time elapses after a handbag style is released. We control a handbag style's age by adding a *STYLEAGE* variable, which counts the number of months that have elapsed since the handbag style's data were first collected. Not all handbag styles are available in the official channels in China at the time of data collection. We use a dichotomous variable, *AVAILABILITY,* where 1 represents that a handbag style is available and 0 otherwise. This variable applies only to the Coach handbag styles because all LV handbag styles are available in China. In addition to the seller reputation heterogeneity considered in the hypotheses, sellers also differ in other dimensions. In the robustness tests of this study, we include two variables, *DISPERSIONST* and *DISPERSIONTQ,* to control seller heterogeneity in seller tenure

Table 2. Price Dispersion at the Style-Month Level

Variables		Obs.	Mean	S.D.	Min.	Max.	t-statistics (H_0: diff < 0)
PD	*PDLP*	3,183	135%	5.14	0	77.69	6.08
	PDTP	854	28.0%	0.327	0	4.04	
CV	*CVLP*	3,183	25.2%	0.547	0	6.07	7.81
	CVTP	854	10.5%	0.114	0	1.14	

(*ST*) and transaction quantity (*TQ*). *ST* represents the number of days that have elapsed since a seller launched his/her store and *TQ* represents the number of handbags sold by a seller in the past month. Both *PD* and *CV* are calculated for *ST* and *TQ* to keep the measures of seller heterogeneity consistent with those of dependent variables. We also add a set of monthly time dummy variables to control the time effect.

When there is only one observation for a handbag style, the values of *PD* and *CV* are zero and null, respectively. Therefore, we exclude observations for styles that had a single transaction or none to ensure that *PD* and *CV* have the same number of observations in the analysis of transaction prices [22]. Table 2 compares the dispersion of listing and transaction prices at the product-month level. For all luxury handbag styles examined in our research, the average *PD* and *CV* of the listing prices are 1.350 and 0.252, respectively. They are 0.280 and 0.105, respectively, for the transaction prices. Smith–Satterthwaite tests show that H1 is supported. This suggests that price dispersion of listing prices is significantly higher than that of transaction prices. In addition, our results indicate that luxury handbags' dispersion of listing prices on Taobao is higher than for most products examined in prior studies, such as airline tickets and books [16, 27, 51]. Such a large variation of listing prices in our study can be attributed to both the product feature (i.e., luxury handbags being high-involvement products) as well as the channel features (i.e., a large number of heterogeneous sellers in the online market).

Econometric Model

We describe the econometric model used to test the proposed hypotheses as follows.

$$\begin{aligned} DISPERSION_{it} = {} & \beta_0 + \beta_1 PRICE_{it} + \beta_2 SELLER_{it} + \beta_3 DISPERSIONSR_{it} \\ & + \beta_4 POPULARITY_{it} + \beta_5 BRAND_i + \sum \alpha_i PRODUCT_i + \varepsilon_{it} \end{aligned}$$

In this study, we have two types of price dispersion for a particular handbag style, one for listing prices and one for transaction prices. We first conduct an exploratory analysis by adding a price type control variable (i.e., *PRICETYPE* = 1 if *DISPERSION* represents the dispersion of listing prices and 0 otherwise) and pool the dispersion of listing and transaction prices together. The results show that price type has a significant impact on price dispersion (see Appendix, Table A1). In order to test our hypotheses and provide a one-to-one comparison of price dispersion between listing and transaction prices, we run the model for two types of prices separately. The coefficients α and β are parameters to be estimated. Tables 3a and 3b present the correlation matrix of the variables.

Statistical tests show that our panel data exhibits heteroskedasticity, and cross-sectional and temporal dependencies. Thus we used pooled ordinary least squares (OLS)/weighted least squares (WLS) and fixed effects regression models with Driscoll and Kraay standard errors [34]. The Driscoll–Kraay nonparametric covariance matrix estimator can produce heteroskedasticity consistent standard errors that are robust to very general forms of spatial and temporal dependence [18, 34]. This estimator is much more robust than OLS, White, Rogers, and Newey–West estimators when the correlation of regression disturbances between handbags is present. This estimator is also adjusted to address the issue of unbalanced panel data insofar as some handbags were not observable on Taobao.com in all eight periods. The results of model estimation are presented in Table 4.

Results

The results indicate that the coefficients of the price level are statistically insignificant in the listing price equation but negative and statistically significant in the transaction price equation. H2a is partially supported. The *t*-test suggests that the coefficient of *PRICE* in the transaction equation is smaller than that of the listing equation, and H2b is also supported. The negative relationship between the dispersion of transaction prices and price level suggests that consumers in our research context are price sensitive. They tend to conduct more intensive search before they buy more expensive items, which leads to the convergence of transaction prices as official prices increase. However, on the supply side, the relationship between the dispersion of listing prices and the price level is statistically insignificant. The individual sellers in microbusiness markets have limited business analytic capability. As a result, they do not fully understand the consumers' search and purchase behavior in the market. Sellers are unclear whether consumers will be more cautious with more expensive items, or their pricing strategies may not change much within a single product category. The weak connection between the consumers' search behavior and the sellers' price-setting decisions may explain why the relationship between the dispersion of listing prices and the price level is insignificant.

Table 4 shows that the coefficients of *SELLER* are positive but statistically insignificant in the listing equation. But in the transaction equation, the coefficients are positive and statistically significant. H3a is not supported but H3b is supported. Luxury handbags are high-involvement products, which demand intensive search before purchase. In addition, sellers in the microbusiness market are often unbranded, which renders prepurchase search particularly important. Search costs significantly increase when the market is flooded with many sellers. As a result, consumers may end up buying from different sellers at varying prices and the

Table 3a. Correlation Matrix of Variables in the Listing Price Equation

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	*PDLP*	1														
2	*CVLP*	0.9378*	1													
3	*PRICE*	0.0225	0.0377*	1												
4	*SELLER*	0.2670*	0.2031*	–0.1620*	1											
5	*PDSR*	0.3984*	0.3488*	–0.0940*	0.6526*	1										
6	*CVSR*	0.2945*	0.2842*	–0.0691*	0.4722*	0.8892*	1									
7	*POPULARITY*	–0.0112	–0.0317	–0.1768*	0.3717*	0.1317*	0.0729*	1								
8	*BRAND*	0.1343*	0.1460*	0.6750*	0.0574*	0.1555*	0.1497*	–0.2055*	1							
9	*STYLEAGE*	0.1814*	0.2014*	–0.0533*	0.1635*	0.3516*	0.3244*	–0.0721*	0.0244	1						
10	*NEWARRIVAL*	–0.0719*	–0.0779*	–0.0326	–0.1877*	–0.1757*	–0.1441*	–0.0077	–0.1874*	–0.3442*	1					
11	*AVAILABILITY*	0.1838*	0.1976*	0.1910*	0.2428*	0.3320*	0.3282*	0.0467*	0.2751*	0.3868*	0.0066	1				
12	*PDST*	0.3601*	0.2799*	–0.0086	0.5987*	0.5286*	0.3854*	0.1768*	0.1845*	0.1340*	–0.1268*	0.1851*	1			
13	*CVST*	0.3080*	0.2459*	–0.0179	0.5089*	0.4911*	0.3960*	0.1254*	0.1997*	0.0920*	–0.1408*	0.1438*	0.9426*	1		
14	*PDTQ*	0.0403*	0.0090	–0.1300	0.6315*	0.2850*	0.1735*	0.4956*	–0.0855*	–0.0342	–0.0710*	0.1019*	0.3519*	0.2761*	1	
15	*CVTQ*	0.0432*	0.0110	–0.1532*	0.6174*	0.2993*	0.1922*	0.4832*	–0.0861*	–0.0513*	–0.0878*	0.0846*	0.3399*	0.2859*	0.9264*	1

***, **, *denote significance at the 0.001, 0.01, and 0.05 levels, respectively.

Table 3b. Correlation Matrix of Variables in the Transaction Price Equation

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	*PDTP*	1														
2	*CVTP*	0.8557*	1													
3	*PRICE*	0.0474	0.0788*	1												
4	*SELLER*	0.5762*	0.3725*	0.0838*	1											
5	*PDSR*	0.3061*	0.2112*	0.1619*	0.5284*	1										
6	*CVSR*	0.2044*	0.1509*	0.1910*	0.3685*	0.9127*	1									
7	*POPULARITY*	0.1509*	0.0249	–0.2887*	0.2621*	–0.0083	–0.0551	1								
8	*BRAND*	0.1714*	0.1947*	0.7570*	0.2155*	0.2821*	0.2911*	0.2779*	1							
9	*STYLEAGE*	0.1541*	0.1547*	0.0256	0.3104*	0.5109*	0.4683*	0.4683*	0.0858*	1						
10	*NEWARRIVAL*	–0.1161*	–0.1124*	–0.1475*	–0.1758*	–0.1487*	–0.1244*	0.0819*	–0.2578*	–0.2745*	1					
11	*AVAILABILITY*	0.1629*	0.1466*	0.0644*	0.3535*	0.3834*	0.3693*	0.0794*	0.0584	0.3684*	0.0712*	1				
12	*PDST*	0.3832*	0.2703*	0.2379*	0.5553*	0.4635*	0.3607*	0.0875*	0.3660*	0.2143*	–0.1216*	0.2405*	1			
13	*CVST*	0.3382*	0.2582*	0.2807*	0.4515*	0.4135*	0.3393*	0.0264	0.4224*	0.1704*	–0.1297*	0.2030*	0.9574*	1		
14	*PDTQ*	0.4008*	0.1700*	–0.1216*	0.5731*	0.2035*	0.1192*	0.4519*	–0.0835*	0.0044	–0.0555	0.1554*	0.2827*	0.2149*	1	
15	*CVTQ*	0.3970*	0.1764*	–0.1311*	0.4759*	0.1686*	0.1001*	0.4019*	–0.0638	–0.0160	–0.0745*	0.1119*	0.2357*	0.1945*	0.9074*	1

***, **, *denote significance at the 0.001, 0.01, and 0.05 levels, respectively.

Table 4. Results for Model Estimation

	Listing prices		Transaction prices		*t*-statistics for hypotheses testing	
	PD	*CV*	*PD*	*CV*	*PD*	*CV*
PRICE ($\times 10^{-6}$)	28.2	–0.0239	–8.79*	–3.57*	39.4	30.0
	(27.8)	(3.04)	(2.78)	(1. 36)		
SELLER	0.00818	0.00177	0.00336***	0.000702***		
	(0.00968)	(0.00112)	(0.000343)	(0.0000586)		
DISPERSIONSR	0.226***	0.114 ***	0.000970	–0.00164	223.6	356.0
	(0.0346)	(0.0126)	(0.00147)	(0.00652)		
POPULARITY	–0.0485	–0.00513	0.000840	–0.000423		
	(0.0306)	(0.00292)	(0.00159)	(0.000363)		
BRAND	0.882	0.143	0.0948*	0.0459*		
	(0.599)	(0.0803)	(0.0319)	(0.0168)		
STYLEAGE	0.164**	0.0300**	0.00901	0.0102*		
	(0.0337)	(0.00705)	(0.00865)	(0.00341)		
NEWARRIVAL	0.504	0.0459	0.0220	0.0137		
	(0.266)	(.0356)	(0.00812)	(0.00766)		
AVAILABILITY	–0.479	–0.0379	–0.0335	–0.00701		
	(0.508)	(0.0474)	(0.0204)	(0.00423)		
INTERCEPT	–1.54**	–0.156	0.0647*	0.0549***		
	(0.442)	(.0776)	(0.0197)	(0.00948)		
N	3,183	3183	854	854		
R^2	0.176	0.122	0.358	0.186		

***, **, *denote significance at the 0.001, 0.01, and 0.05 levels, respectively.

dispersion of transaction prices is positively associated with the number of sellers. On the supply side, our results show that the relationship between the dispersion of listing prices and the number of sellers is insignificant. Compared with buyers, sellers are more aware of the existence of direct competitors and the intensity of price competition in the online market. The competition effect negates the search cost effect to some extent, which results in an insignificant relationship between listing price dispersion and the number of sellers.

The coefficients for seller reputation heterogeneity are positive and statistically significant in the listing price equation but insignificant in the transaction price equation. Therefore, H4a is partially supported. The *t*-test shows that the coefficient of seller reputation heterogeneity in the listing price equation is larger than that of the transaction price equation, and H4b is supported. Good reputation helps establish trust between sellers and buyers in online markets, which enables sellers to charge a price premium. Therefore, the dispersion of seller ratings leads to the dispersion of their listing prices. However, on the demand side, consumers tend to patronize the sellers with reasonably good ratings to reduce transaction risks, especially for high-ticket items like luxury handbags. As a result, the dispersion of seller ratings does not necessarily lead to more dispersed transaction prices.

Our results also indicate that some product-level control variables also affect price dispersion. The coefficients of *STYLEAGE* are positive and statistically significant in the listing equations and in one of the transaction equations. Sellers tend to adjust prices after listing a handbag for a while and consequently buyers purchase the handbag at different prices, leading to higher price dispersion [16, 35]. The coefficients of *BRAND* are positive and statistically significant in the transaction equations, suggesting that transaction prices are more dispersed for LV than for Coach. It is possible that consumer loyalty as well as price sensitivity to different brands differ [33]. To ensure that our results are robust for both brands, we separate our data into the Coach subsample and the LV subsample, and run the analysis for each subsample respectively. The results of hypotheses testing qualitatively hold for both brands. The market feature, *POPULARITY,* and the product features, *NEWARRIVAL* and *AVAILABILITY,* however, do not affect price dispersion significantly in either equation.

Robustness Tests

To examine the robustness of our findings, we conduct several additional tests. Sellers in the microbusiness market are heterogeneous in multiple dimensions in addition to reputation. We therefore conduct two robustness tests to control seller heterogeneity in other dimensions. In the first robustness test, we add a variable, *DISPERSIONST,* to control seller heterogeneity in tenure (see Appendix, Table A2 for the results). In the second robustness test, we add another variable *DISPERSIONTQ* to control seller heterogeneity in selling volume in addition to *DISPERSIONST* (see Appendix, Table A3 for the results). Our results for all hypotheses still hold qualitatively. Interestingly, *DISPERSIONST* and *DISPERSIONTQ* are positively associated with the dispersion of transaction prices but do not affect the dispersion of listing prices, which is in stark contrast to the impacts of seller reputation heterogeneity. These findings suggest that longer seller tenure and higher transaction volume do not help sellers to differentiate themselves from others and to charge a higher price premium. On the demand side, buyers care less about the seller experience and transaction history and buy from sellers that vary dramatically on these two dimensions. We also use a trend variable, *MONTH,* varying from 1 to 8 (i.e., replacing the time dummy variables) to control for any possible seasonality effects during the year. We find that all the results of our hypotheses hold qualitatively (see Appendix, Table A4).

Discussion and Conclusion

Our research reveals two important differences between the dispersion of transaction prices and the dispersion of listing prices. The first is that the magnitude of price dispersion measured by transaction prices is much lower than that measured by listing prices. In particular, the dispersion of transaction prices is only 20 percent (based on *PD*) or 25 percent (based on *CV*) of the dispersion of listing prices in the same market. This difference is largely due to the fact that in the market some listing prices have never been fulfilled, which suggests that some sellers may not have rational expectations about consumer behavior when setting prices. Our result is consistent with Ghose and Yao's [27] observation in an online business-to-business market. It is worth noting that the research contexts in this paper differ from those in Ghose and Yao's paper [27]. Ghose and Yao[27] study a heavily regulated government procurement e-market, where vendors' reputation does not play a major role and buyers' search costs are low. In our research, sellers' reputation scores vary in a wide range and buyers have to search intensively when purchasing high-involvement products. Nevertheless, both papers find that the dispersion of transaction prices is very low, suggesting that the "law of one price" is likely to happen on the demand side of the market. In the Internet age, consumers are well-informed due to abundant information online. Electronic word of mouth and convenient search tools help consumers to discover the price that they need to pay for a product [35, 58]. Consequently, transaction prices are more likely to converge, even though the variation of listing prices from different sellers is still large.

The second distinction is that the drivers of price dispersion are very different between the two sides of the market. This important phenomenon has never been explicitly studied and explained in prior literature. Transaction prices reflect consumers' purchase decisions whereas listing prices represent sellers' pricing decisions. This study shows that information asymmetry exists between the two sides of the microbusiness market.

Sellers, especially microbusiness owners, may not fully understand consumer behavior when they set prices. In this study, consumers are bargain hunters who, to save money, choose to buy luxury handbags from an unauthorized online channel instead of from official retail stores. They engage in more intensive search for more expensive items, hoping to save more [71]. In addition, some higher-end luxury handbags cost more than $1,000, a sixth of an average Chinese gross annual income (www.worldbank.org/en/country/china/overview). Consumers are more cautious when making purchase decisions for these high-end handbags. Therefore, transaction prices are more converged for more expensive handbag styles. However, the results of this study show that sellers' pricing decisions on Taobao.com are not significantly affected by official price levels, which suggests that these sellers may not necessarily understand buyers' expectations and behavior. The owner-managers of microbusinesses tend to use informally absorbed information rather than formal business plans in their decision making [29]. These sellers may not have sufficient analytical capabilities to gain insights into consumer behavior, and hence they end up choosing satisfying rather than profit-maximizing strategies [30]. If sellers are large enterprises, we expect the disparities between the two sides of the market to be smaller.

Our empirical findings highlight two opposite impacts of market concentration on price dispersion. It can reduce price dispersion via intensified market competition, but it can also increase price dispersion because of higher consumer search costs. On the demand side, consumers engage in intensive search for luxury handbags in the online market. When there are more sellers, consumers need to investigate more information, such as sellers' reputation scores, detailed product descriptions, and buyers' comments on prior transactions. Thus, for consumers, the search cost effect associated with the number of sellers dominates the competition effect, and transaction prices diverge more when there are more sellers in the market. However, sellers are more concerned about the competition effect compared with buyers. Sellers are the ones that directly face market competition from their rivals, and the competition effect has a stronger impact on sellers than on buyers. From sellers' perspective, when there are more rivals offering the same products in the market, the competitive pressure in the market cancels out the flexibility to set prices differently due to more costly search. Thus, the number of sellers does not significantly affect the dispersion of listing prices.

Another interesting finding is that seller reputation heterogeneity affects the dispersion of listing prices but not necessarily the dispersion of transaction prices. Seller trustworthiness has long been considered valuable in online markets, and seller reputation is the most important factor affecting online seller choice [63]. Our results confirm that reputation is a key factor when sellers make their pricing decisions. However, on the demand side, it is surprising that seller reputation heterogeneity does not affect the dispersion of transactions prices. It is worth noting that this result does not mean that seller reputation does not matter for buyers. Buyers take seller reputation scores into consideration and tend to patronize reputable sellers. For example, Figure 2 indicates that consumers rarely buy luxury handbags from sellers who have reputation scores lower than 1,000 points. As a result, the variation in sellers' reputation scores is relatively low for successful transactions compared with that of all sellers.

Some limitations must be acknowledged when interpreting the results of this study. In this research, price variation appears on both sides of the market. In industries where listing prices are determined or tightly controlled by manufacturers (e.g., the

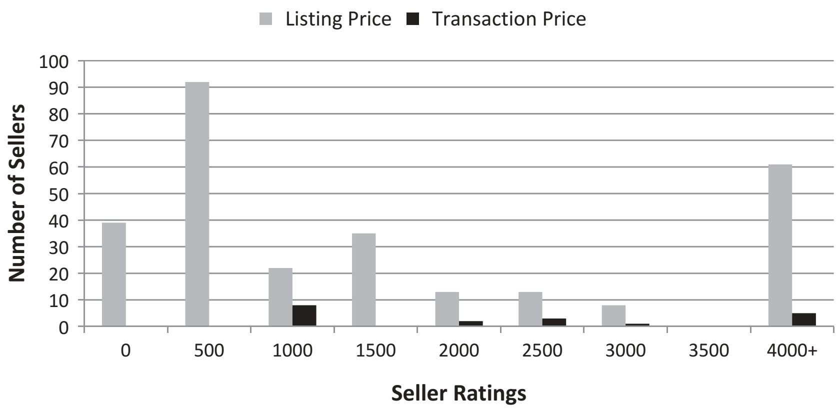

Figure 2. Comparison of seller ratings between listing prices and transaction prices for Coach handbag style 17937

manufacturer's suggested retail price), price dispersion can only occur on the demand side and this makes our findings no longer applicable. Another limitation is that we investigate only a single product category due to data availability. The data collection process was computationally expensive and time consuming, which prevented us from collecting more data from broader product categories. Future research can explore the difference between the dispersion of listing prices and the dispersion of transaction prices in other product categories, and in other types of online markets. Some buyer-related factors, such as buyer heterogeneity, might also affect price dispersion differently between the two sides of the market. However, such variables are not observable in this study. Future research can examine and compare the impacts of the buyer-related factors on price dispersion on both sides of the market. Finally, this study focuses on the market-level dispersion of prices. A possible extension of this work would be to investigate individual sellers' entry and pricing decisions and buyers' purchase decisions in order to gain an in-depth understanding of online market dynamics.

Note

1. Both Taobao Marketplace and Tmall are operated in China by Alibaba Group. Tmall.com was separated from Taobao in 2011 and becomes a business-to-consumer platform for brand owners and authorized distributors.

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Appendix

Table A1. Pooled Dispersion of Listing Price and Transaction Price Together

	PD	*CV*
PRICE ($\times 10^{-6}$)	3.66	–1.30
	(14.5)	(1.75)
SELLER	0.00560	0.00119***
	(0.00306)	(0.000292)
DISPERSIONSR	0.161***	0.0999 ***
	(0.0329)	(0.0193)
PRICETYPE	1.83***	0.200***
	(0.200)	(0.0167)
POPULARITY	–0.0210**	–0.00245***
	(0.00780)	(0.000747)
BRAND	0.652***	0.110***
	(0.157)	(0.0180)
STYLEAGE	0.0978***	0.0215***
	(0.0280)	(0.00432)
NEWARRIVAL	0.256***	0.0253**
	(0.0762)	(.00905)
AVAILABILITY	–0.210*	–0.0176
	(0.103)	(0.0107)
INTERCEPT	–2.53***	–0.280***
	(0.364)	(.0473)
N	4,037	4,037
R^2	0.137	0.114

***, **, *denote significance at the 0.001, 0.01, and 0.05 levels, respectively.

Table A2. *DISPERSIONST* Added to Control Seller Heterogeneity in Experience

	Listing prices		Transaction prices		*t*-statistics for hypotheses testing	
	PD	*CV*	*PD*	*CV*	*PD*	*CV*
PRICE (×10^{-6})	25.5	0.0664	–8.99*	–3.53*	39.0	29.6
	(25.8)	(3.48)	(2.90)	(1. 34)		
SELLER	–0.00542	0.00101	0.00314***	0.000640***		
	(0.00300)	(0.000696)	(0.000312)	(0.0000565)		
DISPERSIONSR	0.193***	0.0985 ***	0.000322	–0.00352	215.6	338.4
	(0.0261)	(0.00815)	(0.00158)	(0.00647)		
POPULARITY	–0.0503	–0.00494	0.000660	–0.000466		
	(0.0275)	(0.00261)	(0.00164)	(0.000360)		
BRAND	0.373	0.103	0.0789*	0.0387*		
	(0.248)	(0.0546)	(0.0296)	(0.0155)		
STYLEAGE	0.151***	0.0288**	0.0104	0.0107*		
	(0.0248)	(0.00634)	(0.00908)	(0.00353)		
NEWARRIVAL	0.399	0.0425	0.0200*	0.0134		
	(0.176)	(.0314)	(0.00838)	(0.00784)		
AVAILABILITY	–0.181	–0.0200	–0.0287	–0.00557		
	(0.266)	(0.0341)	(0.0219)	(0.00457)		
DISPERSIONST	0.142	.0944	0.00217*	0.00890**		
	(0.0649)	(.0470)	(0.000746)	(0.00189)		
INTERCEPT	–1.38**	–0.194	0.0737*	0.0535***		
	(0.332)	(.0956)	(0.0227)	(0.00959)		
N	3,183	3,183	854	854		
R^2	0.2054	0.1330	0.362	0.191		

***, **, *denote significance at the 0.001, 0.01, and 0.05 levels, respectively.

Table A3. *DISPERSIONST* and *DISPERSIONTQ* Added to Control Seller Heterogeneity in Experience and Transaction Quantity

	Listing prices		Transaction prices		*t*-statistics for hypotheses testing	
	PD	*CV*	*PD*	*CV*	*PD*	*CV*
PRICE ($\times 10^{-6}$)	28.0	–0.0198	–8.87*	–3.57*	39.4	30.0
	(27.3)	(3.39)	(3.14)	(1. 34)		
SELLER	0.00394	0.00170	0.00253***	0.000533***		
	(0.00684)	(0.00101)	(0.000294)	(0.000059)		
DISPERSIONSR	0.178***	0.0865 ***	0.00118	–0.00196	223.6	356.0
	(0.0231)	(0.00614)	(0.00161)	(0.00749)		
POPULARITY	–0.0278	–0.00314	–0.000551	–0.000605		
	(0.0184)	(0.00155)	(0.00139)	(0.000315)		
BRAND	0.0320	0.0628 *	0.0626	0.0327		
	(0.226)	(0.0224)	(0.0364)	(0.0156)		
STYLEAGE	0.0888**	0.0188***	–0.00753	0.000991		
	(0.0212)	(0.00372)	(0.00760)	(0.00253)		
NEWARRIVAL	0.242	0.0135	–0.0120	–0.00615		
	(0.120)	(.0184)	(0.0170)	(0.00631)		
AVAILABILITY	0.395	0.0741***	–0.0228	0. 00722		
	(0.117)	(0.0118)	(0.0127)	(0.00478)		
DISPERSIONST	0.145	.0978	0.00241*	0.00993**		
	(0.0622)	(.0452)	(0.000709)	(0.00219)		
DISPERSIONTQ	–0.623	–0.185	0.0269***	0.0134*		
	(0.279)	(0.0914)	(0.00516)	(0.00416)		
INTERCEPT	–1.28**	–0.154	0.0611***	0.0486***		
	(0.340)	(.0806)	(0.0101)	(0.00607)		
N	3,183	3,183	854	854		
R^2	0.2133	0.1415	0.3763	0.1990		

***, **, *denote significance at the 0.001, 0.01, and 0.05 levels, respectively.

Table A4. Use of a Trend Variable (*MONTH*) Varying from 1 to 8

	Listing prices		Transaction prices		*t*-statistics for hypotheses testing	
	PD	*CV*	*PD*	*CV*	*PD*	*CV*
PRICE (×10^{-6})	26.4	–0.0250	–9.04*	–3.72*	40.4	35.6
	(25.6)	(2.93)	(3.07)	(1.49)		
SELLER	0.00860	0.00167	0.00352***	0.000766***		
	(0.0108)	(0.00116)	(0.000375)	(0.0000705)		
DISPERSIONSR	0.220***	0.120 ***	0.000114	–0.00596	198.9	374.5
	(0.0323)	(0.00927)	(0.00146)	(0.00632)		
POPULARITY	–0.0488	–0.00498	0.000550	–0.000488		
	(0.0322)	(0.00299)	(0.00139)	(0.000308)		
BRAND	0.904	0.142	0.0967*	0.0475*		
	(0.630)	(0.0811)	(0.0351)	(0.0173)		
STYLEAGE	0.171**	0.0308**	–0.0168	–0.000379		
	(0.0352)	(0.00711)	(0.00788)	(0.00218)		
NEWARRIVAL	0.510	0.0479	–0.0262	–0.00605		
	(0.289)	(.0390)	(0.0231)	(0.00557)		
AVAILABILITY	–0.476	–0.0366	–0.0354	–0.00740		
	(0.506)	(0.0472)	(0.0203)	(0.00479)		
MONTH	–0.0473	–0.000256	0.0117	0.00276		
	(0.0560)	(0.00651)	(0.00793)	(0.00231)		
INTERCEPT	–1.62**	–0.200*	0.0551*	0.0561***		
	(0.404)	(.0751)	(0.0173)	(0.00834)		
N	3,183	3,183	854	854		
R^2	0.171	0.116	0.341	0.161		

***, **, *denote significance at the 0.001, 0.01, and 0.05 levels, respectively.