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Using Transaction Prices to Re-Examine Price Dispersion in Electronic Markets

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Price dispersion is an important indicator of market efficiency. Internet-based electronic markets have the potential to reduce transaction and search costs, thereby creating more efficient, "frictionless" markets, as predicted by theories in information economics. However, earlier work has reported significant levels of price dispersion on the Internet, which is in contrast to theoretical predictions. A key feature of the existing stream of work has been its use of posted prices to estimate price dispersion. In theory, this can lead to an overestimation of price dispersion because a sale may not have occurred at the posted price. In this research, we use a unique data set of actual transaction prices collected from both the electronic and offline markets of buyers in a business-to-business market to evaluate the extent of price dispersion. We find that price dispersion in the electronic market is as low as 0.22%, which is substantially less than that reported in the existing literature. This near-zero price dispersion suggests that in some electronic markets the "law of one price" can prevail when we consider *transaction* prices, instead of *posted* prices. We further develop a theoretical framework that identifies several new drivers of price dispersion using transaction data. In particular, we focus on four product-level and market-level attributes—product cost, order cycle time, own price elasticity, and transaction quantity, and we estimate their impact on price dispersion. We also examine the electronic market's moderating role in the relationship between these drivers and price dispersion. Finally, we estimate the efficiency gains that accrue from transactions in the relatively friction-free market and find that the electronic market can enhance consumer surplus by as much as $97.92 million per year.

Key words: electronic markets; Internet commerce; price dispersion; transaction prices; demand estimation; consumer surplus; econometrics
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1. Introduction

Bakos (1997) and Bailey (1998) predict that electronic markets would be more efficient and friction-free than traditional markets because of the reduced search costs associated with matching buyers and sellers. Classic Bertrand competition suggests that in perfectly efficient and friction-free markets, prices for homogenous goods will be uniform, resulting in zero price dispersion. However, a vast body of literature has studied price dispersion and found significant levels of price dispersion on the Internet, ranging from approximately 4% to as high as approximately 50% across a wide variety of products. Such price dispersion has generally been attributed to a violation of one of the three Bertrand assumptions: homogeneous sellers and products, zero search costs, and perfectly informed consumers (Salop and Stiglitz 1977, Varian 1980). In particular, earlier empirical literature has identified a variety of retailer, product, and market level factors that lead to price dispersion (Brynjolfsson and Smith 2000; Baye et al. 2004, 2006b; Chen and Hitt 2003; Clemons et al. 2002; Venkatesan et al. 2007).

As some of these studies (Baye et al. 2004, Pan et al. 2004, Venkatesan et al. 2007) have recognized, a common characteristic of the data in earlier research is the use of a product's *posted price* or list price to estimate price dispersion, instead of the *transaction price* at which the goods were actually purchased.

Pan et al. (2004) mention that some retailers bait and switch, i.e., they strategically advertise a low price but do not honor that price. Hence, using posted prices can lead to different estimates of the extent of price dispersion than using transaction prices. To illustrate this, a recent search for the posted prices for a pencil sharpener from the GSA Advantage! Website (the electronic market from which we gathered our data), shows that the posted prices for this product ranged from $35.22 to $47.41. However, the data on actual sales of the same product in our data set reveal that the price dispersion is significantly smaller in magnitude than $12.19, on the order of a few cents. Because a sale could only have occurred at the lowest posted price, none of the higher posted prices might have actually resulted in a sale. Hence, any analysis from such data would lead to an *upper bound* on the actual level of price dispersion. One potential remedy to the data limitation in earlier work is to weight prices by a retailer's popularity, a proxy for sales, as done by Brynjolfsson and Smith (2000). Not surprisingly, they find *less* price dispersion, in terms of weighted prices, on the Internet than in conventional channels. Using unweighted prices, the results are the opposite; that is, price dispersion online is slightly higher than in comparable conventional markets.

Such possibilities motivate the development of a nuanced theoretical framework to better understand the drivers of price dispersion using transaction prices and to estimate price dispersion using transaction data. Transaction prices are market clearing prices and reflect buyers' choices made after observing the various prices offered by different sellers. The current literature has not yet examined these aspects.[1] Toward investigating this phenomenon we use a unique data set of 3.7 million records, encompassing transactions for the Federal Supply Service (FSS) of the U.S. Federal government in fiscal year 2000, to estimate and compare the extent of price dispersion in the FSS' electronic and traditional markets. We also investigate the drivers of price dispersion in electronic and traditional markets and the electronic market's moderating role on these drivers on price dispersion. Furthermore, we seek to understand the increase in consumer surplus from the increased convenience to buyers of searching and purchasing in electronic markets. Using data from the year 2000 also facilitates some comparison of price dispersion levels to earlier findings in literature that mainly used data generated around the same time period.

Besides the fact that the FSS data set gives us access to transaction prices, it also offers a few other advantages. First, the FSS is regulated more closely than the various electronic markets established by online retailers or shopping bots. Unlike most of these markets, vendors in the FSS' electronic market must be certified before participating in any transaction. This vendor screening process can, to a large extent, mitigate the effect of differences in branding or reputation among sellers, which may create potentially confounding effects on the levels of price dispersion. Second, the FSS offers both an Internet-based electronic market and a traditional physical market. The provision of these two markets allows us to examine the differences in price dispersion across these two channels. Because both markets operate within the same context and have the same vendors, this renders better control over other factors that could affect pricing decisions. Finally, the time-series characteristic of the data enables us to evaluate price dispersion for thousands of products in a large number of product categories for a prolonged period of up to a year.

Our paper aims to make the following contributions. First, we develop a conceptual model and formulate hypotheses for analyzing the drivers of price dispersion when using data consisting of transaction prices. In particular, we focus on four market- and product-level attributes—product cost, order cycle time, own price elasticity, and transaction quantity—which have not been studied in earlier literature on price dispersion in their exact form because of the absence of data on actual transactions. Second, we show that when measured using transaction prices, price dispersion in the electronic market can be close to zero. This is substantially lower than that reported in the earlier literature using posted prices but is in accordance with many of the theoretical predictions in the literature on information economics (e.g., the theory of search costs). Our paper thus makes a contribution by highlighting the outcome from using

[1] Some earlier work in financial markets shows that price dispersion continues to exist even when there are institutional buyers (see, for example, Garbade and Silber 1976).

transaction prices to make inferences about price dispersion instead of posted prices. Furthermore, we also show that price dispersion in the electronic market is significantly lower than in the traditional market. This result is consistent with some work in the earlier literature, all of which used posted prices, supporting the theoretical argument that search cost in electronic markets is lower than that in traditional markets (Bakos 1997, Smith and Brynjolfsson 2001, Smith 2001). Given that our findings are different from those in many earlier studies, we point out that our findings should be interpreted in light of the differences in the research settings. Third, because the electronic market also has the potential to increase consumer welfare because of its greater shopping convenience and lower search costs, compared to that of traditional markets, we estimate the efficiency gains accruing from transactions in such friction-free markets. Our analysis reveals that consumer surplus is enhanced by as much as $97.92 million per year because of the availability of the electronic market. This finding thus contributes to the literature on the welfare benefits of the Internet (Brynjolfsson et al. 2003, Ghose et al. 2006, Bapna et al. 2008, Forman et al. 2009). Consistent with an emerging stream of work (Granados et al. 2009), we find that online markets exhibit higher own price elasticity, compared to that of offline markets. Thus, our paper also contributes to the literature that compares demand estimation in electronic markets with that in traditional markets (Chellappa et al. 2007).

The rest of the paper is organized as follows. Section 2 reviews the relevant literature and theory, and it develops hypotheses with a nuanced theory of price dispersion. Section 3 describes the empirical context, data and descriptive analyses. Section 4 presents our econometric analyses and results. Section 5 presents the analysis of consumer welfare estimation. Section 6 discusses our findings. Section 7 concludes the study and discusses its limitations.

2. Theory and Hypothesis

2.1. Literature Review

Two streams of research are relevant to our study. One stream estimates the level of price dispersion online, tests whether online price dispersion is lower than that in offline markets, and examines market and product-level drivers of price dispersion. The second stream of work examines changes in consumer surplus from the introduction of markets and goods. We discuss the relevant work from the first stream in this section and from the second stream in §5.

A growing body of empirical research has examined the issue of price dispersion in electronic markets. All of these studies have found a significant level of price dispersion on the Internet. Based on Pan et al. (2004), we summarize this body of research and its findings in Table 1, with a few modifications. The summary shows that published price dispersion varies greatly, from as low as 4% to as high as 57%.[2] Earlier theoretical and empirical work suggests that price dispersion may result from bundling products with services (Brynjolfsson and Smith 2000, Baye et al. 2004); differences in brand, reputation, and trust across sellers (Brynjolfsson and Smith 2000, Baye et al. 2006, Chen and Hitt 2003); retailer heterogeneity (Smith and Brynjolfsson 2001, Baylis and Perloff 2002, Bailey et al. 1999); product heterogeneity (Baye et al. 2006); price discrimination (Clemons et al. 2002); randomized pricing strategies by firms (Varian 1980, Chen and Hitt 2003, Ghose et al. 2007); interaction between retailer and market characteristics (Venkatesan et al. 2007), multiple channel operations (Ancarani and Shankar 2004, Pan et al. 2003b); and differences in vendor price format such as everyday low prices (EDLP) (Sin et al. 2007, Chellappa et al. 2007).

A number of studies have compared online price dispersion to offline price dispersion. These studies are summarized in Pan et al. (2004). We have reproduced their table in this paper as Table 2, with modifications. Although some studies have found that online price dispersion is higher than offline price dispersion (e.g., Bailey 1998, Brynjolfsson and Smith 2000, Erevelles et al. 2001, Clay et al. 2002), others have found that online dispersion is lower than offline dispersion (e.g., Scott-Morton et al. 2001,

[2] An exception is the work by Ellison and Ellison (2005), which examines price dispersion on the Internet for computer memories using a limited data set of transaction prices collected from Pricewatch.com. They find a price dispersion of 4%, which is much lower than the average reported in other studies.

Table 1 Summary of Empirical Literature on Online Price Dispersion

	Period of data	Percentage difference	Coefficient of variation (%)	Product category
Clemons et al. (2002)	1997	Up to 28		Airline tickets
Bailey (1998)	1997–1998		7.07–17.61	Books, CDs, software
Brynjolfsson and Smith (2000)	1998–1999	25–33		Books, CDs
Clay et al. (2002)	1999	27–73		Books
Clay et al. (2001)	1999–2000	32–65	12.9–27.7	Books
Clay and Tay (2001)	2001	23–42		Books
Baye et al. (2004, 2006)	1999–2001	57*	12.6	Electronics
Baye et al. (2003)	2000–2001	40*	10	Electronics
Scholten and Smith (2002)	2000		12.87–14.5	Grocery and camera, books, flowers, electronics
Pan et al. (2003a, b)	2000–2003	25.70–51.04	7.03–27.1	CDs, DVDs, desktop, laptop, PDA, software, electronics
Ratchford et al. (2003)	2001	15.01–48.08	5.46–16.63	Books, CDs, DVDs, desktop, laptop, PDA, software, electronics
Ellison and Ellison (2005)	2000	4.00**		Computer memories
Baylis and Perloff (2002)	1999	29.00		Consumer electronics
Sin et al. (2007)	2004	30%–46%		Airlines
Chellappa et al. (2007)	2004	30%–46%		Airlines
Baye et al. (2006a)	2004	18%–96%		Books, DVDs, video games, printers, scanners, PDAs.

Source. Pan et al. (2004) with modifications.
*Price range relative to the minimum price, not the average price.
**Price range between the lowest and tenth lowest prices.

Table 2 Summary of Findings in Prior Literature on Online vs. Offline Price Dispersion

Online dispersion higher	Offline dispersion higher	Online and offline dispersion same
Bailey (1998) Brynjolfsson and Smith (2000) Erevelles et al. (2001) Clay et al. (2002) Ancarani and Shankar (2004) (range)	Brynjolfsson and Smith (2000) (market share weighted) Scott-Morton et al. (2001) Brown and Goolsbee (2002) Ancarani and Shankar (2004) (standard deviation) Chellappa et al. 2007	Scholten and Smith (2002)

Source. Pan et al. (2004) with modifications.

Brown and Goolsbee 2002). In addition, Scholten and Smith (2002) study price dispersion in grocery products and cameras and find no significant difference between online and offline price dispersion.[3]

Earlier studies have examined some market and product level drivers of online price dispersion. Pan et al. (2004) present a framework of drivers of online price dispersion, which includes e-tailer characteristics, market characteristics, and product characteristics. In a separate study, Pan et al. (2003a) find that high price dispersion is associated with products with high average prices and few competitors. Venkatesan et al. (2007) find that market characteristics moderate the relationship between retailer characteristics and online price dispersion. Clay et al. (2001) analyze data from the online book industry and conclude that more competition reduces price dispersion and that widely advertised items also have lower prices than less advertised items.

In summary, our approach in this study differs from earlier work in price dispersion in four key ways. First, we use transaction prices, namely, market clearing prices, as opposed to posted prices, to measure and compare price dispersion in both electronic and traditional markets. This allows us to make inferences on the differences in search costs between the two markets. Second, we map the existing sources of price dispersion identified in earlier studies to new market- and product-level variables that are applicable in analyzing transaction price data and

[3] These empirical findings are in tune with theoretical work such as that of MacMinn (1980), who shows the conditions under which price dispersion actually increases when search costs are decreased.

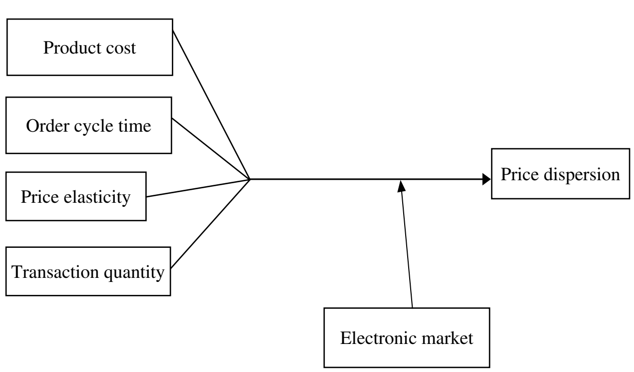
formulate novel hypotheses based on these drivers. This enables us to come up with a nuanced theory of price dispersion that can be examined using data on actual transactions, which has not been done before because of the unavailability of such data. We also delve into an electronic market's moderating role on these drivers. Third, our data allow us to examine four broad product categories (discussed in §3) that include over 17,000 unique products across a 12-month time period. The data are thus much larger in scope than most earlier work. We also examine prices by the *same* set of firms in both online and offline markets over this longitudinal period. With the exception of Chellappa et al. (2007), this is a feature missing in earlier work. *Finally*, earlier work in price dispersion has not linked transaction price data with estimation of buyer surplus in business-to-business (B2B) markets. Our analysis thus sheds some light on the efficiency of these markets.

2.2. Conceptual Model

In addition to quantifying the magnitude of price dispersion, we build a conceptual model to examine the product-level and market-level drivers of price dispersion, as well as the moderating effects of the electronic market. Figure 1 presents the conceptual model.

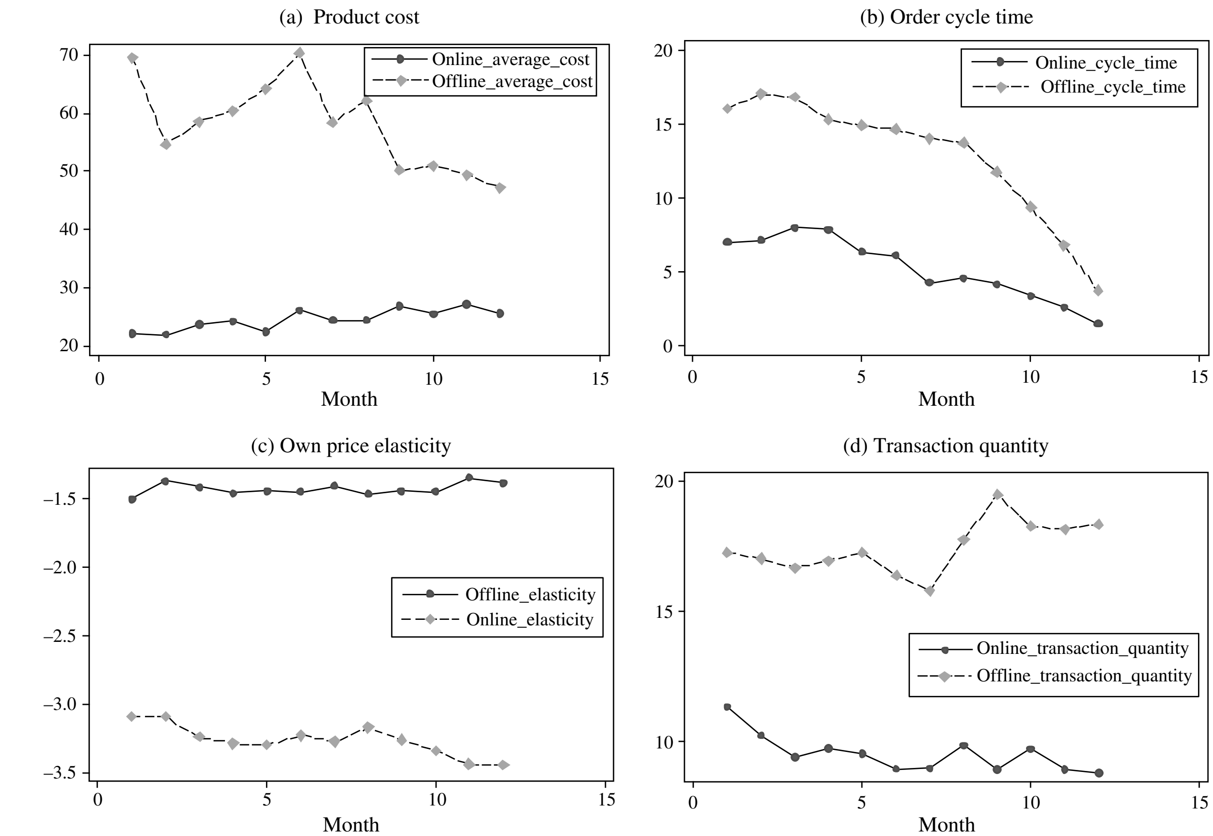
In this paper we focus our analysis on the product-level and market-level characteristics that are available to us based on the data from actual transactions. Our data set has several such attributes: (1) product cost, (2) order cycle time, (3) own price elasticity, and (4) transaction quantity. The *product cost* is the average cost of a product during a selected time frame (week or month). It is a measure of the product value that sellers in B2B or industrial markets can provide to buyers and, hence, strongly correlated with product prices (Goettlieb 1959, Borenstein 1989, Sin et al. 2007). Products with different prices (and thus different average costs) exhibit different levels of price dispersion in both business-to-consumer (B2C), and B2B markets (Sorensen 2000, Stigler and Kindahl 1970). *Order cycle time* is the average time difference in days between when the order for a product is placed and when the product is shipped. It is a measure of service levels for a product across vendors in B2B or industrial markets (Lilien 1987, Ford et al. 2002), which can be a substantial source of price dispersion (Baylis and Perloff 2002). A longer order cycle time implies lower service levels (i.e., a greater possibility of the product being unavailable; Arcelus et al. 2002). *Own price elasticity* measures buyers' sensitivity to changes in the price of a firm's product. It is an indicator of market competitiveness. Because of its potential to affect the final transaction price, own price elasticity can affect price dispersion. Finally, *transaction quantity* is the average quantity for a product over all transactions during a selected time frame (week or month). It is used to assess the effect of order size on price dispersion because the size of the order can affect the transaction price of that product in B2B or industrial markets (e.g., through quantity-based price discounts, which is common in B2B commerce; see, for example, Kelkar et al. 2002).

Figure 1 Conceptual Model



Electronic markets use information and communication technologies to bring buyers and sellers together, transcending geographical and temporal constraints. Compared to traditional markets, electronic markets offer three features that can have important implications on price dispersion. First, electronic markets reduce search costs (Bakos 1997). Smith and Brynjolfsson (2001) and Smith (2001) estimate that search costs in electronic markets may be reduced by "at least 30-fold," compared to those in telephone-based shopping, and even more compared to the price of physically visiting the retailers. Second, electronic markets increase information transparency in both B2C and B2B scenarios (Granados et al. 2009) and reduce information asymmetry (Clemons et al. 1993). For example, electronic markets can increase information availability and processing capability, thus

Figure 2 Variation in Product and Market Characteristics Over Time



facilitating the monitoring of other participants' performance and behavior. Finally, electronic markets expand sellers' reach (Ghose et al. 2006). As a result, a vendor in an electronic market may have a larger customer base than in a traditional market. Because of these features, we also hypothesize that these drivers' impact on price dispersion should differ in electronic markets from that in traditional markets. Figures 2a–e show how these drivers of price dispersion vary over time in electronic and traditional markets.

2.3. Hypothesis

The features described in the conceptual model in §2.2 give rise to the four hypotheses that shape our analysis. We state them in their most succinct form as follows.

As is well known from the literature on industrial marketing and B2B markets (Gottlieb 1959), the average price of a product is correlated with the average cost of the product. This is also true in markets that exhibit both B2B and B2C transactions, for example, airlines (Borenstein 1989, Sin et al. 2007). We motivate our first hypothesis by examining the literature that has analyzed the relationship between product price and price dispersion. Earlier research based on the Weber-Fechner law of psychophysics posits that a response to a change in a stimulus is inversely related to the absolute magnitude of the original stimulus (Grewal and Marmorstein 1994, Monroe 1971). This stream of work has found a positive relationship between price and price dispersion. Grewal and Marmorstein (1994) further argue that consumers engage in less prepurchase searching for high-priced items (durables) than for low-priced items because they view savings in relative versus absolute terms. As the price of an individual item goes up, consumers value the relative savings less than before and, as a consequence, they spend little time in price comparison shopping. The aggregate effect of this lack of price comparison shopping for big-ticket items is likely to increase price dispersion. Lindsey-Mullikin and Grewal (2006) consistently demonstrate that as the mean price of an item increases, price dispersion also increases. Earlier work in economics, information systems and marketing also find a positive relationship between price and price dispersion. Pratt et al. (1979) and, more recently, Clay et al. (2001) and Smith (2001) have found a positive relationship between product price and price dispersion. There are other examples in markets in which both B2C and B2B transactions may occur. For example, in Internet car retailing, Scott-Morton et al. (2001) show that prices on Autobytel are lower and exhibit lower variance than other competitors. In industrial markets, Stigler and Kindahl (1970) show that prices affect price dispersion in the hydraulic cement industry. Because price is positively correlated with cost (Gottlieb 1959), we posit a positive relationship between price dispersion and product cost.

Electronic markets not only reduce buyers' search costs but also increase sellers' market reach and, consequently, increase their ability to tap more consumers (Ghose et al. 2006). Earlier research has shown that the market expansion effect may dominate the competitive effect resulting from more searches, thereby leading to higher price dispersion. For example, Samuelson and Zhang (1992) show that a decrease in search costs increases price levels and price dispersion. A decrease in search costs has two effects. First, it increases consumers' ability to sample firms to look for an alternative, which reduces prices. Second, it increases the number of consumers that sample a firm's products (i.e., increases demand), which raises prices. If the second effect dominates the first, price dispersion increases. Cachon et al. (2007) also show that while making searches easier intensifies competition, it also gives firms access to more consumers than previously, thereby increasing prices. They further demonstrate that the market expansion effect can dominate the competition, intensifying effect leading to higher price dispersion. Kuksov (2004) draws similar conclusions. An examination of our data shows that the number of buyers of higher-priced products in the electronic market (23,879) is greater than that in the traditional market (20,681),[4] suggesting that the market expansion effect resulting from the use of the electronic market may be a key driver of price dispersion in our setting.[5] Because price is correlated with cost, products with higher cost are likely to exhibit greater price dispersion in the electronic market than in the traditional market. Therefore, we have the following hypothesis.

Hypothesis 1 (H1). *Products with higher cost are associated with higher price dispersion. Moreover, this effect is reinforced in an electronic market.*

The presence of service quality differentiation has been cited as a source of price dispersion in electronic markets because different levels of service are typically associated with different levels of prices (Betancourt and Gautschi 1993, Smith et al. 2000, Baylis and Perloff 2002, Pan et al. 2002, Cao et al. 2003, Cao and Gruca 2004). Betancourt and Gautschi (1993) find that service quality significantly affects price dispersion in traditional markets, such that firms with higher service quality charge higher prices. Smith et al. (2000) discuss that shopping convenience and reliability in fulfillment, which are two examples of service quality, contribute to price variation in electronic markets. Pan et al. (2002), who investigate the role of vendor service quality as an antecedent to price dispersion, find partial support for the effects of e-tailer service quality's effects on price. Cao et al. (2003) indicate that consumers are willing to pay higher prices if they are satisfied with ordering or fulfillment processes and, in this context, Chellappa et al. (2007) find that higher reservation prices for tickets with higher overall quality are associated with higher levels of price dispersion, along the lines of Varian (1980). Venkatesan et al. (2007) find that a high-service quality retailer can seek similar high premiums in markets with potential for service differentiation. They suggest that in product markets at higher price levels, retailers who foster trust by way of better service quality are afforded scope for price differentiation and would charge relatively higher. In

[4] Among the total number of buyers in our data, 1,221 are dual channel buyers.

[5] We categorize high- versus low-priced products, using both the mean and median values of the products' price. Both yielded consistent results. The number displayed above is the result using the mean. Moreover, on visualizing the data, we also see some evidence that the number of buyers has been growing over time in the electronic market.

the context of *GSA Advantage*!, service quality level may be evident in the order cycle time patterns of different products. A longer-order cycle time implies lower degree of product availability or lower service quality levels, reducing the number of buyers of such products and the scope for differentiation for those sellers.[6] This leads sellers to reduce prices which, in turn, results in lower price dispersion (Pratt et al. 1979, Clay et al. 2001, Scott-Morton et al. 2001, Venkatesan 2007). Earlier literature in B2B markets has also suggested that order cycle time is an intrinsic characteristic of industrial markets (Lilien 1987, Ford et al. 2002) and that differences in order cycle times lead to differences in product prices (Arcelus et al. 2002).

Product availability differences among sellers can be private information and hard to find in a traditional market. However, in electronic markets such as *GSA Advantage*!, such information is made available to all buyers before purchase. When product availability information is private, all sellers tend to charge similar prices (for example, an inferior seller with low product availability can also pretend to be a superior one and charge a high price). Because of increased supplier transparency in electronic markets (Granados et al. 2009), sellers are likely to set their price based on their actual service level, thereby resulting in greater price dispersion. This is particularly true for products with longer order cycle times, because these products tend to have a greater variation in offerings among sellers than do products with shorter order cycle times.[7] Thus, we posit that electronic markets will moderate the decrease in price dispersion because of an increase in the order cycle time. Therefore, we have the following hypothesis.

Hypothesis 2 (H2). *Products with longer order cycle times are associated with lower price dispersion. However, this effect is moderated in an electronic market.*

Various papers in the literature on competition on the Internet have analyzed the own price elasticity of offers listed at shopbots and shopbot-like marketplaces (Baye et al. 2004, Ellison and Ellison 2005, Ghose et al. 2006). Elasticity measures at Internet shopbots are relevant in our context, because the display of information at these services is comparable to the information displayed on the FSS' electronic market. Own price elasticity is an indicator of market competitiveness. A decrease in product or seller level differentiation generally leads to a higher own price elasticity because buyers become more sensitive to the changes in the price of a seller for a given product. Because most products in our data are commodities, and all sellers are pre-screened for quality, there is very little differentiation among sellers or products. This lack of differentiation increases the own price elasticity of demand and leads to lower equilibrium prices. Because an increase in own price elasticity lowers the average price of products (Perloff and Salop 1985), it leads to lower levels of price dispersion (Pratt et al. 1979, Clay et al. 2001, Scott-Morton et al. 2001, Gatti and Kattuman 2003). Walsh and Whelan (1999), among others, have adopted the notion of heterogeneous demand elasticity as a key source of price dispersion. Barron et al. (2004) show that an increase in the own price elasticity of demand will result in a decrease in the average markups. This will lead to a reduction in price dispersion, as the increase in own price elasticity lowers prices of all sellers toward their respective marginal costs. Earlier literature in B2B markets has also suggested that price elasticity is a characteristic of industrial markets (Lilien 1987). Hence, we posit that price dispersion would decrease with an increase in own-price elasticity.

Furthermore, because the density of sellers is typically much higher in online markets than in traditional markets for most commodity products (Ghose et al. 2006), own price elasticity should be higher in the online world, because it is easier there for buyers to search across multiple sellers' offerings than in the offline market. Other studies, such as those of Ellison and Ellison (2005) and Granados et al. (2009), also find that prices in electronic markets are more elastic than in traditional markets because of increased market transparency and competition. Hence, we expect that the inverse relationship between own price elasticity

[6] Descriptive statistics from our data show that this is indeed the case. Using the mean value to split order cycle time into long and short values, we found that products with longer order cycle times had 39,585 buyers, whereas products with shorter order cycle times had 63,578 buyers.

[7] For example, the correlation between order cycle time and order cycle time gap is high, at 0.39, as shown in Table 7.

(i.e., a buyer's sensitivity to the change in the price of a seller) and price dispersion to be even stronger in electronic markets than in traditional markets. Thus, we have the following hypothesis.

Hypothesis 3 (H3). *Products with higher own price elasticity are associated with lower price dispersion. Moreover, this effect is reinforced in an electronic market.*

It is well known from the theories of second-degree price discrimination (Tirole 1988) that sellers often offer a menu of contracts with different price and quantity offers. These offers are based on traditional nonlinear pricing or quantity discounts that price the marginal unit lower than the average unit. In such instances, high-volume buyers often receive a quantity-based price discount from sellers. Earlier literature in B2B markets have suggested that transaction quantity is a characteristic of industrial markets (Lilien 1987, Webster 1991, Wilson 1999) and that differences in transaction quantities in a given order lead to differences in product prices (Arcelus et al. 2002, Kelkar et al. 2002). There are several examples of these practices documented in earlier work in B2B or industrial markets. In a study of wholesale purchases by institutional buyers (such as drugstores and hospitals) in the pharmaceutical market, Scott-Morton (1997) find that products that face competition in a molecular market have high levels of price dispersion caused by quantity-based price discounting. Reuters and Caulkins (2004) discuss that volume discounts are positively related to price dispersion in the drug industry, and other studies such as those of Nieberding and Cantor (2007), also suggest the same relationship. In our research setting, some sellers offer volume discounts for a given product, whereas others do not. Furthermore, even among the sellers who offer volume discounts, their discounting schemes differ across products. Therefore, price dispersion is higher when transaction quantity is high than when transaction quantity is low, because of the diversity in the volume discounts offered for different products.

Although an increase in transaction quantity is expected to increase price dispersion, this effect is likely to be greatly moderated by the electronic market because of increased price transparency and lower search costs for buyers to parse through the offerings of different sellers of a given product. For example, a greater proportion of buyers can find the best volume discount schemes in electronic markets than they can in traditional markets, leading to smaller price dispersion. Hence, we have the following hypothesis.

Hypothesis 4 (H4). *Products with higher transaction quantity are associated with higher price dispersion. However, this effect is moderated in an electronic market.*

3. Empirical Context, Data, and Descriptive Analysis

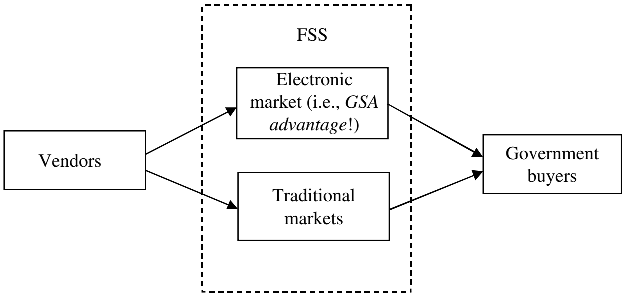
3.1. The FSS Markets

The FSS, which acts as an intermediary, is a core component of the U.S. government's supply chain. The FSS is designed to match buyers from a large number of government agencies to a variety of vendors. Both buyers and vendors are certified by the U.S. government. Vendors must meet a rigorous set of standards to qualify for inclusion in the GSA's supply business or on the federal supply schedules. The FSS and the contracted commercial vendors provide government buyers with access to more than four million products and services.

The FSS system includes an electronic market (i.e., the Internet-based *GSA Advantage*!) and a traditional market that allows placing orders over the phone, by fax and by proprietary electronic data interchange systems, as well as physical stores. The electronic market was introduced in 1997 and was soon recognized as one of the world's largest online ordering and tracking system. It provides a convenient way for federal purchasers to browse, compare, and order products online. As of 2001, *GSA Advantage*! offered more than two million products and had 312,000 registered users, among which were 149,000 customers identified as frequent buyers (compared to one-time shoppers); 20,000 were identified as large, powerful buyers (i.e., those who transact in large quantities) (GSA 2001). The number of browsers using the catalog sites has been estimated at around 1,250,000 annually. Figure 3 presents the structure of the FSS' markets.

All buyers have access to both the electronic and traditional markets, and all vendors are required to support both the electronic and traditional markets.

Figure 3 The Structure of FSS' Markets



A key difference between the electronic and traditional markets is the availability of a search engine in the electronic market that facilitates product and vendor searches. The electronic market lists products side by side on the screen so that buyers can easily engage in price comparison shopping. In this sense, the electronic market plays a role similar to that of shopbots in the B2C markets such as shoppers.com, dealtime.com, etc. In the traditional market, government buyers obtain price information by looking up products in paper catalogs. Because of the additional convenience of shopping in the electronic market, the final product and transaction bundle experienced by buyers in the electronic market differ from those available in the offline market. Moreover, despite the fact that most buyers were government buyers, they were not required to purchase only from the lowest price vendor at the time the data was gathered. In this respect, the transactions in our data set are similar to those in other commercial markets.

3.2. Data Description

The data consist of the FSS' transaction and fulfillment records of goods shipped during fiscal year 2000. The source data consist of 3.7 million records, each corresponding to one purchase order and fulfillment. Given the diversity of its products, we include in our analysis only product categories with more than 100,000 transactions per year. This criterion yields four product categories, as defined by FSS. They are as follows: hand tools and hardware (category 1); office supplies and devices (category 2); brushes, paints, sealers, and adhesives (category 3); and containers, packaging, and packing supplies (category 4). The total number of transactions in these product categories accounts for approximately 85% of the total records.

To measure price dispersion, we define the unit of measurement along two dimensions. One is by product and the other is by time. Because our data are based on transaction records, we aggregate the transactions at the product level. The FSS system uses the national stock number (NSN), a 13-digit number, to uniquely identify a product. Because our data identify the date of each transaction, we can measure price dispersion at the week and month level. That is, we can conduct analyses at the product-week and product-month levels.[8] The final aggregated data include 328,945 and 152,988 observations, respectively, at the product-week and product-month levels. Because the qualitative nature of our results from the product-week level is very consistent with those from the product-month level, we focus our discussion primarily on the product-month level estimates, for brevity.

Table 3 presents descriptive statistics on the number of observations by product categories, aggregated at the week and month levels, and in the electronic and traditional markets. Table 3 shows that all product categories have a substantial number of transactions occurring through either the electronic market or the traditional market, with a higher proportion of transactions occurring through the traditional market. Furthermore, the four product categories are quite distinct in the extent of their sales on the electronic market (e.g., more sales of office supplies and devices than sales of containers, packaging, and packing supplies) and represent different levels of product homogeneity (e.g., office supplies and devices are likely to be more homogenous than other product categories). Therefore, including multiple categories in our analysis can increase the robustness of our results.

3.3. Descriptive Analysis

The price in the data set is the amount a buyer pays for one unit of an item. It is the total of the item's price and shipping cost. Earlier research has suggested that Internet retailers manipulate products'

[8] At the month level, the average number of transactions for a product is 17.64 in the traditional channel and 10.35 on the Internet. At week level, it is 8.88 for the traditional channel and 7.55 for Internet channel.

Table 3 Number of Observations in Electronic and Traditional Markets

	Product-week		Product-month	
	Electronic market	Traditional market	Electronic market	Traditional market
Hand tools and hardware	14,969 (4.55%)	95,793 (29.12%)	10,497 (6.86%)	47,505 (31.05%)
Office supplies and devices	75,354 (22.91%)	94,901 (28.85%)	30,234 (19.76%)	39,616 (25.89%)
Brushes, paints, sealers, and adhesives	3,251 (0.99%)	26,099 (7.93%)	2,696 (1.76%)	13,487 (8.82%)
Containers, packaging, and packing supplies	5,397 (1.64%)	13,181 (4.01%)	2,938 (1.92%)	6,015 (3.93%)
Total	328,945 (100%)		152,988 (100%)	

price and shipping charges to gain a competitive advantage (Dinlersoz and Li 2006). Measuring total cost (i.e., a product's price and shipping charges), as done by Brynjolfsson and Smith (2000) and Pan et al. (2002, 2003a), can eliminate potential price dispersion resulting from such manipulation. We use two metrics that are widely used in the literature, percentage price difference (PD) and coefficient of variation (CV) to measure price dispersion. PD is defined as the highest transaction price minus the lowest transaction price for a product, among all transactions during a week or month, divided by the mean price. CV is defined as the ratio of the standard deviation of a product's prices during a week or month over its mean price. Both PD and CV are calculated using transaction records from the electronic and traditional markets. As a result, we have two sets of PDs and CVs, one for the electronic market and one for the traditional market, for each product-time level of analysis. It is worth noting that PD and CV have different numbers of observations. If a product has only one transaction in a given time period, the calculation of PD yields a value of 0, whereas the calculation of CV yields a missing value (CV exists only for a sample of more than two observations). For example, at the product-month level, PD and CV have 226,194 and 152,988 observations, respectively. Thus, we exclude observations for products that had only a single transaction during a given period of time when performing our analyses. This is a conservative way to present our result, because price dispersion is even smaller when including those observations.

Table 4 Average Price Dispersion at Week and Month Level (in Percentage)

	Product-week		Product-month	
	PD	CV	PD	CV
Electronic market	0.43	0.22	1.29	0.52
Traditional market	6.62	2.70	9.81	3.31
t statistics (H_0: diff $= 0$)	116***	105***	85***	82*

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

Table 5 Number of Zero and Non-Zero Price Dispersion

	Product-week		Product-month	
	Zero	Nonzero	Zero	Nonzero
Electronic market	96,176	2,795	43,932	2,433
Traditional market	180,899	49,075	73,590	33,033
Total	328,945		152,988	

Table 4 shows price dispersion measured by PD and CV at the product-week and product-month levels. Note that the table shows little price dispersion in either the electronic or traditional market. At the product-month level of analysis, the PD and CV in the electronic market are 1.29% and 0.52%, respectively. In the traditional market they are 9.81% and 3.31%, respectively. A t test rejects the null hypothesis that the difference in price dispersion between the electronic and traditional markets is equal to 0, indicating that price dispersion in the traditional market is significantly larger than in the electronic market. In addition, price dispersion is generally smaller when measured at the weekly level than when measured at the monthly level because the longer the time period, the greater the temporal price dispersion.

Similar to Table 4, Table 5 shows the number of zero and nonzero price dispersions measured by PD and CV at the week and month levels.[9] From Table 5 we find that only a small percentage of products exhibit price dispersion. For example, at the product-month level, only 2,433 of 152,988, or 1.59% of products transacted in the electronic market, have nonzero levels of price dispersion as measured by either PD

[9] The number tracks the products during a specific period (week or month) and shows whether there is any variation in transaction prices during that period. If a product's price does not vary during the period, it yields a value of zero.

or CV, whereas in the traditional market, 33,033 of 152,988, or 21.59% of products transacted, display positive price dispersion.

4. Econometric Model

We describe the econometric models used to estimate and compare price dispersion between the electronic and traditional markets (Model 1) and to test our proposed hypotheses (Model 2). As discussed earlier, we separate records based on whether a transaction occurred in the electronic or traditional market. Then we aggregate the transaction records to product-time (week or month) level. That is, for a particular product over a particular unit of time (week or month), we have two observations of price dispersion, one for the electronic market and one for the traditional market. Let i denote product, j denote market, and t denote time. We estimate models of the following form:

Model 1

$$PD_{ijt} = \beta_0 + \beta_1 EM_j + \beta_2 COST_{ijt} + \beta_3 CYCLE_{ijt} + \beta_4 E_{ijt} + \beta_5 QTY_{ijt} + \beta_6 QTYGAP_{ijt} + \beta_7 CYCGAP_{ijt} + \beta_8 TIME_{ijt} + \sum_{k=1}^{3} \alpha_k CAT_{kj} + \varepsilon_{ijt}. \tag{1}$$

$$CV_{ijt} = \beta_0 + \beta_1 EM_j + \beta_2 COST_{ijt} + \beta_3 CYCLE_{ijt} + \beta_4 E_{ijt} + \beta_5 QTY_{ijt} + \beta_6 QTYGAP_{ijt} + \beta_7 CYCGAP_{ijt} + \beta_8 TIME_{ijt} + \sum_{k=1}^{3} \alpha_k CAT_{kj} + \varepsilon_{ijt}. \tag{2}$$

Model 2

$$PD_{ijt} = \beta_0 + \beta_1 EM_j + \beta_2 COST_{jt} + \beta_3 CYCLE_{ijt} + \beta_4 E_{ijt} + \beta_5 QTY_{ijt} + \beta_6 QTYGAP_{ijt} + \beta_7 CYCGAP_{ijt} + \beta_8 TIME_{ijt} + \sum_{k=1}^{3} \alpha_k CAT_{kj} + \beta_9 X_{ijt} + \varepsilon_{ijt}. \tag{3}$$

$$CV_{ijt} = \beta_0 + \beta_1 EM_j + \beta_2 COST_{ijt} + \beta_3 CYCLE_{ijt} + \beta_4 E_{ijt} + \beta_5 QTY_{ijt} + \beta_6 QTYGAP_{ijt} + \beta_7 CYCGAP_{ijt} + \beta_8 TIME_{ijt} + \sum_{k=1}^{3} \alpha_k CAT_{kj} + \beta_9 X_{ijt} + \varepsilon_{ijt}. \tag{4}$$

EM is an indicator variable denoting whether a transaction was conducted in the electronic or traditional market. The product cost (*COST*), order cycle time (*CYCLE*), own price elasticity (*E*), and transaction quantity (*QTY*) are defined in §2. The only difference between Models 1 and 2 is that Model 2 adds an interaction term (*X*) between *EM* and one of the following variables: *COST, CYCLE, E*, and *QTY*. The interaction term tests the moderating effect proposed in our hypotheses.

We include a number of control variables in both models. In particular, we include transaction quantity gap (*QTYGAP*) and order cycle time gap (*CYCGAP*) to control for alternative sources of price dispersion resulting from demand variation and service differences for a product during a given time frame. *QTYGAP* is the difference in transaction quantity between the largest and the smallest quantity of product transacted during a time period. It is used to control for the effect of demand variation on price dispersion because demand adversely affects price (e.g., through volume discounts). *CYCGAP* is the difference in cycle time between the longest and the shortest order times for a product during a time period and is included to control for the effect of heterogeneity in service levels across the vendors. *TIME* is a trend variable[10] (from 1 to 52 for product-week level analysis and from 1 to 12 for product-month level analysis) included to control for any possible seasonality effects during the year. Because we have four product categories, we include three dummy variables (*CAT*) to control for unobserved category-level effects. Finally, ε is the disturbance term, and αs and βs are parameters to be estimated.

4.1. Results: Model 1—Estimation of Price Dispersion

Table 6 presents the descriptive statistics, and Table 7 presents the correlation matrix for the variables at the product-month level.[11] The dependent variables PD and CV are either zero or a positive number. Moreover, the percentage of data points that equal zero is

[10] We also estimated time dummies (i.e., replaced the trend variable with a series of time dummies) to control for seasonality. The results were consistent with our current results and are omitted for brevity.

[11] For the sake of brevity, the product-week level statistics are not presented. To check for potential multicollinearity, we compute variance inflation factor (VIF) scores for all independent variables. The VIF scores for all independent variables are between 1.01 and 5.19, lower than the commonly accepted level of 10 (Kennedy 2003).

Table 6 **Descriptive Statistics (Product-Month Level)**

	Electronic market					Traditional market				
	N	Mean	S.D.	Min.	Max.	*N*	Mean	S.D.	Min.	Max.
1. Price difference (PD)	46,365	0.013	0.15	0	13.79	106,623	0.10	0.22	0	16.27
2. Coefficient of variation (CV)	46,365	0.05	0.05	0	2.52	106,623	0.03	0.08	0	3.23
3. Electronic market (*EM*)	46,365	1	0	1	1	106,623	0	0	0	0
4. Product cost (*COST*) ($)	46,365	18.15	46.32	0.02	1,328	106,623	46.97	410.94	0.03	58,699
5. Order cycle time (*CYCLE*)	46,365	5.15	12.64	0	277	106,623	13.21	21.18	0	303
6. Own price elasticity (*E*)	46,365	−3.27	4.82	−22.4	8.06	106,623	−1.43	2.42	−13.1	0.22
7. Transaction quantity (*QTY*)	46,365	9.46	26.75	1	1,196	106,623	17.40	69.66	1	7,503
8. Transaction quantity gap (*QTYGAP*)	46,365	3.63	5.57	0	137.8	106,623	4.72	9.19	0	415.9
9. Order cycle time GAP (*CYCGAP*)	46,365	10.17	18.37	0	331	106,623	19.28	23.83	0	350
10. Hand tools and hardware	46,365	0.23	0.42	0	1	106,623	0.45	0.50	0	1
11. Office supplies and devices	46,365	0.65	0.48	0	1	106,623	0.37	0.48	0	1
12. Brushes, paints, sealers, and adhesives	46,365	0.06	0.23	0	1	106,623	0.13	0.33	0	1
13. Containers, packaging, and packing supplies	46,365	0.06	0.24	0	1	106,623	0.06	0.23	0	1

larger than what we would expect under a normal distribution. For example, at the month level of analysis, 117,497 observations are zeros, accounting for 76.80% of all cases. This suggests that the PD and CV variables have a censored distribution; that is, they are left-censored at zero. For a censored dependent variable, OLS estimates are econometrically inconsistent (Greene 1999) and, hence, inappropriate in our setting. A Tobit model accounts for such censored distribution, thereby resulting in consistent estimates (Amemiya 1973, Greene 1999). The Tobit technique uses all observations, both those at the limit and those above it, to estimate a regression line, and it is to be preferred, in general, over alternative techniques that estimate a regression only with the observations above the limit (McDonald and Moffitt 1980). Hence, we use Tobit regressions. Furthermore, we report robust standard errors to alleviate any concerns about the impact of heteroskedasticity on the estimates from the Tobit model.

The Tobit results for Model 1 are presented in Table 8. At the product-week level, the coefficients for the electronic market are negative and statistically significant ($\beta = -0.60$ and $p < 0.001$ in the PD equation, $\beta = -0.27$ and $p < 0.001$ in the CV equation), indicating that the price dispersion in the electronic market is lower than that in the traditional market. Similarly, at the product-month level, the coefficients for the electronic market are negative and statistically significant ($\beta = -0.62$ and $p < 0.001$ in the PD equation, $\beta = -0.22$ and $p < 0.001$ in the CV equation). The consistency of the coefficients across both

Table 7 **Correlation Matrix (Product-Month Level)**

	1	2	3	4	5	6	7	8	9	10	11	12	
1. Price difference (PD)	1												
2. Coefficient of variation (CV)	0.89	1											
3. Electronic market (*EM*)	−0.19	−0.17	1										
4. Product cost (*COST*) ($)	0.08	0.09	−0.04	1									
5. Order cycle time (*CYCLE*)	0.01	0.05	−0.19	0.08	1								
6. Own price elasticity (*E*)	0.03	0.02	−0.25	−0.04	0.004	1							
7. Transaction quantity (*QTY*)	0.09	0.10	−0.06	−0.02	0.01	0.02	1						
8. Transaction quantity gap (*QTYGAP*)	0.22	0.09	−0.06	−0.04	−0.11	0.06	0.09	1					
9. Order cycle time GAP (*CYCGAP*)	0.20	0.16	−0.18	0.02	0.39	0.04	0.04	0.21	1				
10. Hand tools and hardware	−0.11	−0.12	−0.21	0.03	0.07	0.07	−0.08	−0.09	−0.05	1			
11. Office supplies and devices	0.12	0.13	0.26	−0.02	−0.11	−0.11	0.04	0.13	−0.02	−0.72	1		
12. Brushes, paints, sealers, and adhesives	−0.05	−0.05	−0.10	−0.01	0.08	0.06	0.04	−0.06	0.09	−0.27	−0.32	1	
13. Containers, packaging, and packing supplies	0.03	0.05	0.01	−0.01	−0.01	−0.00*	0.03	−0.01	0.02	−0.19	−0.23	−0.09	1

*Denotes insignificance. The rest coefficients are significant at the 0.001 level.

Table 8 Results of Tobit Estimations (Model 1)

	Column (1)		Column (2)	
	Product-week		Product-month	
	PD	CV	PD	CV
Intercept	−0.45***	−0.20***	−0.30***	−0.10***
	(0.01)	(0.003)	(0.02)	(0.004)
Electronic market (*EM*)	−0.60***	−0.27***	−0.62****	−0.22***
	(0.01)	(0.003)	(0.02)	(0.003)
Product cost (*COST*) ($\times 10^{-6}$)	76.90***	31.70***	68.40***	24.00***
	(15.60)	(6.02)	(19.10)	(5.77)
Order cycle time (*CYCLE*) ($\times 10^{-3}$)	−1.06***	−0.27***	−2.86***	−0.68***
	(0.13)	(0.05)	(0.19)	(0.06)
Own price elasticity (*E*) ($\times 10^{-3}$)	−1.61*	−0.60*	0.43	0.17
	(0.73)	(0.31)	(0.84)	(0.31)
Transaction quantity (*QTY*) ($\times 10^{-3}$)	0.20**	0.10***	0.43***	0.20***
	(0.06)	(0.03)	(0.07)	(0.03)
Transaction quantity gap (*QTYGAP*) ($\times 10^{-3}$)	2.36***	7.93***	9.96***	2.45***
	(0.60)	(0.19)	(0.46)	(0.12)
Order cycle time GAP (*CYCGAP*) ($\times 10^{-3}$)	5.43***	2.29***	5.78***	1.93***
	(0.16)	(0.05)	(0.22)	(0.05)
Time (*TIME*) ($\times 10^{-3}$)	2.12***	0.97***	8.86***	3.07***
	(0.09)	(0.04)	(0.61)	(0.21)
Category dummy: hand tools and hardware	−0.31***	−0.15***	−0.33***	−0.13***
	(0.08)	(0.03)	(0.01)	(0.003)
Category dummy: office supplies and devices	0.04***	0.02***	0.04***	0.01***
	(0.005)	(0.002)	(0.01)	(0.003)
Category dummy: brushes, paints, sealers, and adhesives	−0.31***	−0.15***	−0.34***	−0.13***
	(0.01)	(0.003)	(0.01)	(0.004)
N	328,945	328,945	152,988	152,988
Log likelihood	−97,378	−56,837	−59,608	−24,616
Pseudo R^2	0.26	0.34	0.24	0.41

Note. Robust standard errors are listed in parentheses; ***, **, and * denote significance at 0.001, 0.01, and 0.05, respectively.

levels demonstrates the robustness of our results. We then use these Tobit estimates to predict price dispersions in the electronic and traditional markets, while keeping other variables at their means. Table 9 presents the predicted price dispersion. The numbers are consistent with those in Table 4, showing that price dispersion in the electronic market is close to zero and is significantly smaller than that in the traditional market.

The coefficients for *TIME* are positive and significant, suggesting that price dispersion tends to grow larger over time. This is consistent with Pan et al. (2002), who show that e-tailer and market characteristics become more influential drivers of price dispersion among retailers over time. Our analysis shows

Table 9 Predicted Average Price Dispersion from Tobit Model (in Percentage)

	Product-week		Product-month	
	PD	CV	PD	CV
Electronic market	0.56	0.25	1.29	0.47
Traditional market	6.36	2.72	10.37	3.66
t statistics (H_0: diff $= 0$)	306***	353***	249***	278***

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

that price dispersion increases over time, suggesting that buyers in this market do not seem to exhibit any potential learning over time. The coefficients for *QTYGAP* and *CYCGAP* are both positive and statistically significant, indicating that products with high variation in transaction quantity and order cycle time are associated with high price dispersion. This result suggests that differences in transaction quantity and order cycle time are possible sources of price dispersion. This could be attributed, for example, to volume discounts offered by some vendors and differential service levels across vendors. After controlling for these potential sources of price dispersion, our results show that the level of price dispersion in the electronic market is close to 0 and that price dispersion in the offline market is higher than in the electronic market. Because *COST*, *CYCLE*, *E*, and *QTY* are hypothesized and tested in Model 2, we discuss them in §4.3.

4.2. Robustness Tests

To validate the robustness of our estimations we performed several different robustness checks. First, we ran OLS models with product-fixed effects at both the product-week and product-month levels. Those results are also consistent with the results reported and are shown in Table SA1 in the online appendix.[12] For example, at the product-month level, the price dispersion is 0.52% and 3.31% in online and offline markets, respectively, based on the CV metric. Second, to address concerns about different buyers buying different products across the two channels, we have estimated the models after including only the transactions with common products that were sold in

[12] Additional information is contained in an online appendix to this paper that is available on the *Information System Research* website (http://isr.pubs.informs.org/ecompanion.html).

both channels. In particular, we have done these analyses using the top-100 common products (by sales), top-500 common products, top-1,000 common products, top-5,000 common products, and all common products (7,283) in online and offline channels. We have run these analyses for both the CV and the PD at both the product-week and product-month level of analysis. The results are consistent with those in Table 9, and the results for all common products are presented in Table SA2 in the online appendix. For example, at the product-month level, the price dispersion is 0.42% and 4.39% in online and offline markets, respectively, based on the CV metric. We have also estimated the model based on the sample of common buyers who bought across both channels to address concerns about different buyers selecting different channels. Those results are also consistent with those presented in Table 9 and are presented in Table SA3 in the online appendix. For example, at the product-month level and based on the CV metric, price dispersion is 0.35% and 0.86% in online and offline markets, respectively. Third, we excluded all repeat purchases for each buyer and analyzed the subsample of single purchases. This was motivated by the possibility that buyers may have low propensity to conduct a thorough search for repeat purchases. As a result, they might keep buying from the same source, thereby resulting in little price dispersion. The results are consistent with those in Table 9 and are presented in Table SA4 in the online appendix. For example, at the product-month level, the price dispersion is 0.57% and 1.84% in online and offline markets, respectively, based on the CV metric. Fourth, to alleviate concerns about the impact of variation in shipping costs by transaction quantity on price dispersion, we have estimated the models after splitting the sample by transactions involving high and low transaction quantities. Those results are also consistent with those presented in Table 9 and are presented in Tables SA5 and SA6 in the online appendix. For example, for the sample involving low transaction quantities, at the product-month level, the price dispersion is 0.95% and 1.49% in online and offline markets, respectively, based on the CV metric. Fifth, in response to concerns about the year 2000 as a unique year, we have examined the results by splitting the sample into two six-month subsamples, as well as four quarterly subsamples. The results are consistent with those reported in Table 9 and are presented in Tables SA7 and SA8 in the online appendix. For example, at the product-month level, the price dispersion is 0.42% and 3.94% in online and offline markets, respectively, based on the CV metric from the analysis of the sample in the first half of the year. The empirical estimates from the semiannual analyses are presented in Table SA16. Sixth, to alleviate concerns on the presence of GSA transactions, we have performed a number of analyses by isolating the impact of GSA's stock program from the transactions involving direct sales by vendors. The results are consistent with those reported in Table 9 and are presented in Table SA9 in the online appendix. For example, at the product-month level, the price dispersion is 0.68% and 0.88% in online and offline markets, respectively, based on the CV metric from the analysis of the sample consisting of direct vendor sales only (non-GSA transactions). The empirical estimates from the non-GSA analysis are presented in Table SA17. Seventh, to check for additional ways to rank top-selling products, we have used the number of distinct buyers of the product to rank products. The results are consistent with our main results when we use "sales volume in dollars" to rank products and are presented in Table SA10–SA12 in the online appendix. For example, at the product-month level for the top-100 common products, the price dispersion is 0.27% and 4.98% in online and offline markets, respectively, based on the CV metric. Finally, the most extreme form of filtering we have used is only for those products (i) that have sufficient observations during a month, (ii) that are common across both offline and online channels, and (iii) that have transactions for a sufficient number of months. This is a three-step rigorous filtering process gradually reducing the large sample into a small but highly relevant sample. The results are consistent with those reported in Table 9 and are presented in Tables SA13–SA15 in the online appendix. For example, at the product-month level, the price dispersions for the common products sold in both channels with an average of more than 10 observations during a month and having been transacted at least 6 months out of a year are 0.42% and 6.70% in online and offline markets, respectively, based on the CV metric.

Table 10 Results of Tobit Estimations (Model 2 at Product-Month Level)

	Column (1)		Column (2)		Column (3)		Column (4)		Column (5)	
	Hypothesis 1		Hypothesis 2		Hypothesis 3		Hypothesis 4		Full model	
	PD	CV	PD	CV	PD	CV	PD	CV	PD	CV
Intercept	−0.30***	−0.10***	−0.29***	−0.10***	−0.30***	−0.10***	−0.30***	−0.10***	−0.29***	−0.10***
	(0.02)	(0.004)	(0.02)	(0.004)	(0.02)	(0.004)	(0.02)	(0.004)	(0.02)	(0.004)
Electronic market (*EM*)	−0.64***	−0.23***	−0.68***	−0.25***	−0.61***	−0.22***	−0.61***	−0.22***	−0.69***	−0.25***
	(0.02)	(0.004)	(0.02)	(0.004)	(0.02)	(0.004)	(0.02)	(0.004)	(0.02)	(0.004)
Product cost (*COST*) ($\times 10^{-6}$)	65.80***	23.10***	69.40***	24.40***	68.30***	24.00***	68.40***	24.00***	67.50***	23.70***
	(18.6)	(5.58)	(19.3)	(5.83)	(19.1)	(5.77)	(19.1)	(5.77)	(19.0)	(5.72)
Order cycle time (*CYCLE*) ($\times 10^{-3}$)	−3.02***	−0.73***	−3.63***	−0.95***	−2.86***	−0.68***	−2.86***	−0.68***	−3.65***	−0.95***
	(0.19)	(0.06)	(0.21)	(0.06)	(0.19)	(0.06)	(0.19)	(0.06)	(0.21)	(0.06)
Own price elasticity (*E*) ($\times 10^{-3}$)	0.18	0.08	−0.94	−0.32	0.29	0.12	0.42	0.17	−0.85	0.28
	(0.84)	(0.31)	(0.85)	(0.31)	(0.9)	(0.34)	(0.84)	(0.31)	(0.94)	(0.34)
Transaction quantity (*QTY*) ($\times 10^{-3}$)	0.43***	0.20***	0.43***	0.20***	0.43***	0.20***	0.44***	0.20***	0.44***	0.20***
	(0.08)	(0.03)	(0.08)	(0.03)	(0.07)	(0.03)	(0.08)	(0.03)	(0.08)	(0.03)
Transaction quantity gap (*QTYGAP*) ($\times 10^{-3}$)	10.00***	2.47***	9.98***	2.46***	9.96***	2.45***	9.97***	2.45***	10.02***	2.47***
	(0.47)	(0.12)	(0.46)	(0.12)	(0.46)	(0.12)	(0.46)	(0.12)	(0.47)	(0.12)
Order cycle time GAP (*CYCGAP*) ($\times 10^{-3}$)	5.82***	1.95***	5.66***	1.89***	5.78***	1.93***	5.78***	1.93***	5.70***	1.90***
	(0.2)	(0.05)	(0.22)	(0.05)	(0.2)	(0.05)	(0.22)	(0.05)	(0.22)	(0.05)
Interaction term of *EM* and *COST* ($\times 10^{-3}$)	1.20***	0.42***							0.83***	0.29***
	(0.09)	(0.03)							(0.08)	(0.03)
Interaction term of *EM* and *CYCLE* ($\times 10^{-3}$)			7.14***	2.49***					6.44***	2.25***
			(0.42)	(0.14)					(0.42)	(0.15)
Interaction term of *EM* and *E* ($\times 10^{-3}$)					0.47	0.15			−0.62	−0.23
					(2.2)	(0.79)			(2.14)	(0.79)
Interaction term of *EM* and *QTY* ($\times 10^{-3}$)							−0.52*	−0.17*	−0.36+	−0.11
							(0.24)	(0.08)	(0.21)	(0.07)
Time (*TIME*) ($\times 10^{-3}$)	8.81***	3.05***	8.93***	3.10***	8.86***	3.07***	8.84***	3.07***	8.89***	3.08***
	(0.61)	(0.21)	(0.62)	(0.21)	(0.61)	(0.2)	(0.61)	(0.21)	(0.62)	(0.21)
Category dummy: hand tools and hardware	−0.33***	−0.13***	−0.33***	−0.13***	−0.33***	−0.13***	−0.33***	−0.13***	−0.33***	−0.13***
	(0.01)	(0.003)	(0.01)	(0.003)	(0.01)	(0.003)	(0.01)	(0.003)	(0.01)	(0.003)
Category dummy: office supplies and devices	0.04***	0.01***	0.03***	0.01**	0.04***	0.01***	0.04***	0.01***	0.03***	0.01***
	(0.01)	(0.003)	(0.01)	(0.003)	(0.01)	(0.003)	(0.01)	(0.003)	(0.01)	(0.003)
Category dummy: brushes, paints, sealers, and adhesives	−0.34***	−0.13***	−0.34***	−0.13	−0.34***	−0.13***	−0.34***	−0.13	−0.34***	−0.13***
	(0.01)	(0.004)	(0.01)	(0.004)	(0.01)	(0.004)	(0.01)	(0.004)	(0.01)	(0.004)
N	152,988	152,988	152,988	152,988	152,988	152,988	152,988	152,988	152,988	152,988
Log likelihood	−59,476	−24,499	−59,322	−24,352	−59,608	−24,617	−59,604	−24,614	−59,262	−24,299
Pseudo R^2	0.24	0.41	0.25	0.42	0.24	0.41	0.24	0.41	0.25	0.42

Note. Robust standard errors are listed in parentheses; ***, **, and * denote significance at 0.001, 0.01, and 0.05, respectively.

4.3. Results: Model 2—Drivers of Price Dispersion

We also estimate Model 2 at product-week and product-month levels. Table 10 presents the estimation results at the product-month level.[13] Column (1) presents the results of assessing the effect of product cost. The coefficient for *COST* is positive and significant ($\beta = 65.80 \times 10^{-6}$ and $p < 0.001$ in the PD equation, $\beta = 23.10 \times 10^{-6}$ and $p < 0.001$ in the CV equation), and the coefficient for the interaction term of *COST* and *EM* is also positive and significant ($\beta = 1.2 \times 10^{-3}$ and $p < 0.001$ in the PD equation, $\beta = 0.42 \times 10^{-3}$ and $p < 0.001$ in the CV equation). These results lend support to both parts of Hypothesis 1, which proposes that price dispersion is higher

[13] The pseudo R-squared statistics for all estimations of Models 1 and 2 are between 0.22 and 0.41, indicating a good fit for these regression estimations. Because of space constraints, the product-week level results are omitted but are available on request.

for products with higher product costs than for products with lower product costs, an effect reinforced by the electronic market.

Column (2) presents the results of assessing the effect of order cycle time. The coefficient for *CYCLE* is negative and significant ($\beta = -3.63 \times 10^{-3}$ and $p < 0.001$ in the PD equation, $\beta = -0.95 \times 10^{-3}$ and $p < 0.001$ in the CV equation), and the coefficient for the interaction term of CYCLE and EM is positive and significant ($\beta = 7.14 \times 10^{-3}$ and $p < 0.001$ in the PD equation, $\beta = 2.49 \times 10^{-3}$ and $p < 0.001$ in the CV equation), indicating that price dispersion is lower for products with longer order cycle time than for products with shorter order cycle time in the traditional market. However, this effect is significantly moderated in the electronic market, such that price dispersion is higher for products with a longer order cycle time than for products with a shorter order cycle time in the online channel, suggesting that the electronic market plays an important role in facilitating information transparency. These results lend support to Hypothesis 2 in the traditional market but not in the electronic market. The moderating effect of Hypothesis 2, however, is supported.

Column (3) presents the results of assessing the effect of own price elasticity. Notice that the coefficient of *E* is significant and negative in product-week level analysis in Table 8, supporting the first half of Hypothesis 3. Moreover, when we run the various robustness tests, such as those at the product-week level analyses, we find that the coefficient of *E* and the interaction term is significant and negative. However, in Table 10, the coefficients for both *E* and the interaction term are generally insignificant, suggesting that Hypothesis 3 is unsupported at the product-month level but supported at the product-week level. Thus, Hypothesis 3 is partially supported.

Column (4) presents the results of assessing the effect of transaction quantity. The coefficient for *QTY* is positive and significant ($\beta = 0.44 \times 10^{-3}$ and $p < 0.001$ in the PD equation, $\beta = 0.20 \times 10^{-3}$ and $p < 0.001$ in the CV equation), but the coefficient for the interaction term of *QTY* and *EM* is negative and significant ($\beta = -0.52 \times 10^{-3}$ and $p < 0.05$ in the PD equation, $\beta = -0.17 \times 10^{-3}$ and $p < 0.05$ in the CV equation). These results lend support to Hypothesis 4 based on the results of the CV equation, which posits that price dispersion is higher for products with higher transaction quantity. However, based on the results of PD equation, this effect on PD is significantly moderated by the electronic market such that, in the electronic market, price dispersion is higher for products with a lower transaction quantity than for products with a higher transaction quantity. This result, again, highlights the important role of the electronic market in facilitating information transparency. Table 11 summarizes our results.

Finally, column (5) presents the estimation results from the full model, which included all interaction terms. The qualitative nature of the main results remains unchanged. The only change is that the interaction of electronic market and transaction quantity is now statistically insignificant at the product-month level in the CV equation, although it is in the right direction. However, in our robustness checks, we see that the interaction continues to remain statistically significant at the product-week level.

5. Implications for Consumer Welfare

One impact of reduced price dispersion in electronic markets is that it increases consumer welfare. None of the previous studies in the literature, as discussed in Pan et al. (2004), could estimate the implications of reduced price dispersion for consumer welfare

Table 11 **Main Hypotheses and Summary of Results**

Hypothesis	Relevant coefficients	Prediction	Supported?	Location
Product cost	Product cost	Positive	Supported	Table 8 and 10, Row 3
	Product cost ∗ Electronic market	Positive		Table 10, Row 9
Order cycle time	Order cycle time	Negative	Partially	Table 8 and 10, Row 4
	Order cycle time ∗ Electronic market	Positive	Supported	Table 10, Row 10
Own price elasticity	Price elasticity	Negative	Partially	Table 8 and 10, Row 5
	Own price elasticity ∗ Electronic market	Negative	Supported	Table 10, Row 11
Transaction quantity	Transaction quantity	Positive	Supported	Table 8 and 10, Row 6
	Transaction quantity ∗ Electronic market	Negative		Table 10, Row 12

because of the data limitation arising from the absence of transaction prices. They assert that "[i]f most sales in online markets take place at relatively low prices, and high price sellers have relatively low volumes, price dispersion could cost consumers much less if a high share of sales takes place at relatively high prices." Using transaction prices, we address this question by estimating the impact of reduced price dispersion on consumer welfare.

A stream of research on developing techniques to estimate welfare effects from the introduction of new goods is based on the compensating variation measure of Hicks (1942). This technique has been applied to measure welfare gains from new goods ranging from increased product variety on the Internet (Brynjolffson et al. 2003) to the establishment of used-good markets (Ghose et al. 2006). Following their approach, in this section we apply the methodology of Hausman and Leonard (2002) estimate the electronic market's impact on consumer surplus.

To impute this, we need to estimate the own price elasticity of demand. Hence, we estimate models at transaction level with Log(*SALES*) as the dependent variable and Log(*PRICE*) as the independent variable. Note that the unit of analysis is a transaction, which is different from that used in the analyses of price dispersion. *SALES*, therefore, is defined as the total quantity of a product sold in a transaction. The control variables include the order cycle time (*CYCLE*), time trends (*DATE*), and product category dummies (*CAT*). We estimate the regressions separately for the electronic and traditional markets. Consistent with earlier studies of Internet-based demand (Chevalier and Goolsbee 2003, Ghose et al. 2006), we use a log-linear model,

$$Ln(SALES) = \alpha_0 + \alpha_1 Ln(PRICE) + \alpha_2 CYCLE + \alpha_3 DATE + \sum_{k=1}^{3} \alpha_k CAT_{kj} + \varepsilon, \qquad (5)$$

where α_1 is the own price elasticity of demand, *CAT* represents the dummy variables for each product category, *CYCLE* and *DATE* are control variables, and ε is a random error term. Column (1) in Table 12 present the OLS results.

Because of the potential endogeneity of price, we also estimate the model using a two-stage least-square (2SLS) with instrument variables. The instrumental variables are annual sales volume, total transaction frequency for a product during the year, and a seller-level shipping warehouse dummy that serves as a proxy for cost. Because the annual sales volume and total transaction frequency are product-level variables, they are correlated with price but unlikely to be correlated with unobserved vendor heterogeneity. The shipping warehouse dummy variable identifies the shipping warehouse of GSA versus other sellers in our sample. Besides controlling for vendor heterogeneity, this cost-side variable is a valid instrument because it is correlated with prices but is uncorrelated with the error term. The intuition is that different sellers have warehouses situated in different locations and, hence, their cost structure would be different because of differences in warehouse rental and maintenance costs and inventory carrying costs. As a result, this variable is likely to be correlated with prices but uncorrelated with unobservable factors that affect sales, as is well known in the literature (for example, Berry 1994).

Table 12 Elasticity Estimates for Electronic Markets

	Column (1)	Column (2)
	OLS	2SLS
Intercept	2.18***	5.31***
	(0.01)	(0.025)
Transaction price (*PRICE*)	−0.32***	−1.47***
	(0.001)	(0.01)
Order cycle time (*CYCLE*)	0.003***	0.012***
	(0.0001)	(0.0001)
Date ($\times 10^{-3}$)	−0.05***	0.3***
	(0.01)	(0.01)
Category dummy: hand tools and hardware	−0.43***	−1.80***
	(0.01)	(0.01)
Category dummy: office supplies and devices	−0.31***	−1.59***
	(0.01)	(0.01)
Category dummy: brushes, paints, sealers, and adhesives	0.16***	−0.89***
	(0.01)	(0.01)
N	813,606	813,606
Adjusted R^2	0.12	0.06

Note. Robust standard errors are listed in parentheses; ***, **, and * denote significance at 0.001, 0.01, and 0.05, respectively.

Column (2) in Table 12 presents the results from the 2SLS estimation.[14] All of the coefficients are signifi-

[14] Pairwise correlations between variables were much lower than the 0.8 critical level suggested by Kennedy (2003). A VIF test also revealed that there was no concern for multicollinearity.

cant at the 0.01% level. The results indicate that the average own price elasticity in the electronic market is −1.47. Based on a similar analysis for the offline market, we find that own price elasticity in the offline market is −0.84. This implies that the demand in the electronic market is more elastic than in the traditional market. These estimates are consistent with the conclusions of earlier studies, which find that prices in electronic markets are generally more elastic than in traditional markets because of increased efficiency and market transparency (Ellison and Ellison 2005, Granados et al. 2009). In particular, Granados et al. (2009) find that own price elasticity for online travel agencies is −1.29, whereas for offline travel agencies it is −0.82.[15]

Having estimated the own price elasticity, we follow the approach used by Ghose et al. (2006) to estimate the gain in consumer surplus attributable to the use of the electronic market. This approach was originally developed by Hausman and Leonard (2002) to calculate the consumer surplus gain from the introduction of new goods, and it was further simplified by Brynjolfsson et al. (2003) to estimate the surplus arising from the availability of products that represent a small proportion of overall expenditures, so that the effect of income elasticity can be ignored. In our data, the expenses incurred by government agencies to buy these products (e.g., office products, hand tools, and packaging supplies) usually constitute a tiny proportion of their overall budget. Therefore, we use the following formula (Brynjolfsson et al. 2003, Ghose et al. 2006) to compute the consumer surplus gain from the use of the electronic market:

$$CS = \frac{p_e q_e}{1+\eta_e}, \qquad (6)$$

where p_e q_e represents the total sales in dollars of the products in the electronic market, and η_e is the own price elasticity of demand.

Although we know that the electronic market was introduced more recently than the offline market and that the former provides buyers with additional utility from its greater shopping convenience,[16] it is possible that some buyers still consider the offline market as a perfect substitute for the online market, especially those who buy across both channels. To alleviate this concern, we run our analysis on a smaller sample of transactions to underestimate the gains in buyer welfare. In particular, we exclude transactions that were conducted by buyers who have purchased products in both channels and include transactions by buyers who have purchased only in the electronic market over the one-year period. The main idea is that in the absence of the electronic market these buyers would either have been forced to buy these products in the offline market, or they would have refrained from buying these products at all. This sample of transactions results in an own price elasticity of −1.52 in the electronic market. Based on the revenues accruing from these transactions ($50.92 million) across the four product categories, the final consumer welfare gain from the electronic market works out to be $97.92 million per year, which is almost twice as much as the revenues from these transactions.

Our consumer surplus estimate is comparable to the estimate in Ghose et al. (2006), who find that the online used-book market on Amazon.com increases consumer surplus by $67.21 million per year. However, it may be worth noting that the consumer surplus in Ghose et al. (2006) amounted to only one fourth of the total revenues from transactions in the used-book market. Furthermore, in our data, the revenues accruing from the buyers who use traditional channels only are $376 million. If the buyers were to spend all of that in the electronic market of *GSA*

[15] We have also experimented with a different set of instruments. Specifically, we used GMM-based estimators as in the studies of Arellano and Bond (1991), Blundell and Bond (1998), and Arellano and Bover (1995). Arellano and Bond (1991) developed a GMM estimator that treats the model as a system of equations, one for each time period. The equations differ only in their instrument/moment condition sets. These are dynamic panel data estimators, and they have used lagged first-differences as instruments for equations in levels, along with combinations of lagged levels as instruments for equations in first-differences. The own price elasticity in the electronic market in these analyses ranges from −1.35 to −1.51 and is thus consistent with our main estimates.

[16] Examples of such additional utility creating differences across the two markets include searching for items using keywords, part numbers, manufacturer names, contractor names, or contract numbers; browsing by category of products and services; comparing features, prices and delivery options; configuring products and adding accessories; reviewing delivery options; selecting a convenient payment method; and viewing order history to track status, reorder, or cancel.

Advantage!, based on our calculation, the total consumer surplus gains could be as high as $723.07 million. These numbers are in the range of the estimates shown by Brynjolfsson et al. (2003), who find that the increased product variety of online bookstores enhanced consumer welfare by $731 million to $1.03 billion in the year 2000, which is the same time frame as that of our data. However, one needs to keep in mind that Brynjolfsson et al. (2003) and Ghose et al. (2006) analyzed B2C electronic markets whereas our buyer surplus estimates are for a B2B electronic market.

6. Discussion

The magnitude of price dispersion in the electronic market in our study is much lower, compared to that reported in previous studies. Most previous studies have found that average price dispersion is between 20% and 30% when measured by price gap or range and between 5%–20% when measured by coefficient of variation (e.g., Pan et al. 2004). In our research, we find price dispersion to be less than 1% under a number of different scenarios.

Our results merit some discussion toward understanding why the estimated price dispersion is so low when we use transaction price to measure it. Earlier studies (Brynjolfsson and Smith 2000; Pan et al. 2002, 2003a, b; Baye et al. 2004) have recognized that, when using posted prices to measure price dispersion, some outliers (low-end prices) may not be honored by retailers once a customer comes to the market, and other outliers (high-end prices) may not generate any sales at all. These outliers contribute to price dispersion measured by posted prices but not to that measured by transaction prices. Moreover, *GSA Advantage*! is more closely regulated than many of the commercial electronic markets studied in earlier work, which, to a large extent, mitigates unobserved heterogeneity among vendors in terms of brand or reputation effects. Finally, we have studied price dispersion in a single electronic market. *GSA Advantage*! is the only source for government buyers to purchase their office supplies on the Internet. Thus, these buyers' search costs are arguably low. Given that our B2B setting is different from that in many earlier studies that are based on B2C scenarios, we would like to point out that our findings should be interpreted in light of the differences in the research settings.

We also find that price dispersion in the electronic market is significantly lower than in the traditional market. Because we use transaction prices, namely, market clearing prices, this finding suggests that buyers in the electronic markets can more efficiently locate the lower prices because of reduced search costs, thus providing empirical support to the theoretical prediction that electronic markets have lower search costs (Bakos 1997). Previous empirical studies have not conclusively shown whether electronic or traditional markets have higher price dispersion. Rather, the evidence is quite mixed. Our paper makes a contribution by providing empirical evidence using transaction prices, which has not been done before.

Using transaction data, we have studied four product and market level drivers. In particular, we analyze the impact of product cost, order cycle time, own price elasticity, and transaction quantity on price dispersion. We find that high value products (those having a high product cost) are associated with higher price dispersion than are low cost products. This finding suggests that in some B2B markets the effect of the Weber-Fechner law of psychophysics can indeed be greater than the effect of increased searches for high value products. This effect is even stronger in the electronic market than in traditional markets, indicating that the market expansion effect resulting from the electronic market dominates the competition-intensifying effect resulting from reduced search costs in the electronic market. The finding that products' price dispersion falls as their own price elasticity increases is consistent with results from earlier studies, which show that increased competition reduces price dispersion. To our knowledge, our study is the first attempt to directly use own price elasticity to measure competition and link it with price dispersion. Finally, we find that price dispersion is negatively associated with order cycle time in the traditional market but positively associated with it in the electronic market, and that price dispersion is positively associated with transaction quantity, although the effect becomes weaker in the electronic market than in the traditional market. Future research can explore the validity of these insights in a B2C electronic market, such as shopping bots or in markets established by online retailers.

Furthermore, we estimate demand to infer own price elasticities toward estimating the increase in consumer surplus. Consistent with an emerging stream of work on demand estimation in electronic markets, we find that online markets exhibit higher own price elasticity, compared to that of offline markets. This finding is consistent with the theory that in more price-transparent channels such as markets, own price elasticity is relatively higher, whereas for more product transparent channels such as offline markets, own price elasticity is relatively lower (Lynch and Ariely 2000, Granados et al. 2009). Although our calculations of welfare focus on buyer surplus, retailers also face several countervailing effects. On the one hand, they may gain from the additional sales they make because of the complementarity between the offline and online channels. On the other hand, they may also suffer from the cannibalization of online sales by the offline channel, or vice-versa. Furthermore, although retailers may benefit from the wider market coverage created by the electronic market, they may also lose from increased competition because of higher price and supplier transparency. It would be interesting to use transaction data to explore implications for retailer welfare in future research.

7. Conclusion

In this research we first estimate and compare the magnitude of price dispersion using transaction price in both an electronic market and a traditional market. We then develop a nuanced theoretical model and test a number of hypotheses on both market- and product-level drivers of price dispersion and the moderating role of the electronic market. We use a data set collected from the FSS of GSA, which consists of their transaction records in both the electronic and traditional markets. We demonstrate that price dispersion has indeed been reduced to negligible levels in some electronic markets—a finding contrary to earlier empirical studies but in accordance with several theoretical predictions in information economics.

Although our data provide many advantages in estimating price dispersion, compared to those used in earlier studies, the study also has some limitations. One limitation is that we study price dispersion in a single electronic market. Many other studies (e.g., Brynjolfsson and Smith 2000) collected price data from individual websites of multiple Internet retailers. Conceivably, buyers' search costs can be higher for sequential searches across individual Internet retailers, compared to a shopbot-like electronic market, leading to higher price dispersion. Nonetheless, it is worth noting that some studies (e.g., Baye et al. 2004, 2006) that collected posted price data directly off a shopbot have reported much higher levels of price dispersion than our study. Another limitation is that the data do not identify the vendors; that is, we cannot attribute each transaction to a particular vendor. Thus, we have limited controls for vendor heterogeneity. A similar data limitation has also been acknowledged in earlier work, such as that of Baye et al. (2006). Such data unavailability does prevent us from evaluating the drivers of price dispersion in terms of market structure, which could interact with retailer characteristics, as pointed out by Venkatesan et al. (2007). Despite these limitations, we hope that our research paves the way for future research in this area.

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