

**Price, Price Dispersion, Arbitrage and the Law of One Price: A Comparison of
Online and Physical Wholesale Vehicle Auctions**

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Abstract

We used a unique dataset of 30,533 off-lease vehicle auction sales (10,898 offline and 19,635 online) to examine the economic impact of adding an Internet sale channel to a firm's existing channel portfolio. Our findings suggest that an Internet channel adds economic benefit in several ways. First, the data suggest that prices are significantly higher and that the dispersion of prices for vehicles sold is significantly narrower in the online channel than in the offline channel. In addition, the price difference observed between vehicles sold via online and offline channels is greater than one would expect to see from reduced transaction costs alone. Our data suggest that there are significant differences in the prices obtained for vehicles across locations and that these differences are associated with the flow of vehicles between states with vehicles flowing from low cost states to higher cost states. Finally, we show that the range of online prices is narrower than the range of offline prices. These findings are consistent with the suppositions that online prices converge more closely toward a national price than offline prices and that the online channel may allow the firm to capture a portion of the arbitrage rents.

Keywords: Price levels, price dispersion, arbitrage, law of one price, online markets

1. Introduction

The introduction of an electronic mechanism into a market may cause important changes in the way that market operates. This paper examines the economic impact of adding an Internet sale channel to a firm's existing channel portfolio. Previous empirical research comparing the efficiencies of online and offline markets has largely focused on settings where posted-prices are used as the sale mechanism (e.g., Brynjolfsson & Smith, 2000; Clay et al. 2002; Pan et al. 2004; Baye et al. 2004). By contrast, assessing differential performance outcomes in (online vs. physical) auction settings has received relatively little attention to date. Specifically, using a proprietary data set of 30,533 wholesale pre-owned vehicle auction sales (19,635 through an online venue and 10,898 through 35 offline physical venues) obtained from one seller (the financial services arm of a large auto manufacturer), we examine price levels and price dispersion in both online and offline sales channels and assess the economic impact of the online auction market.

Differences in price levels and price dispersion in posted-price settings are posited on account of differences in search cost. The search costs in the wholesale auction setting we examine here are different from those in multi-seller fixed-priced settings and include the costs required to locate a product (i.e., a vehicle) that closely matches the buyer's preferences and the buyer's transaction costs of participating in the bidding process. In the traditional auction setting, these costs reduce buyers' ability to participate in vehicles auctions held too far from home and these buyer costs are lower in the online market than in the traditional market. In addition, online users can also more easily observe the behavior of other market participants. As a result, vehicles sold online may be less likely to

be affected by regional market forces and preferences, and may be more likely to be sold at a “nation price”, since buyers compete without regard to geography.

Our empirical analysis provides evidence showing that an Internet auction channel is more efficient, and that this enhanced market efficiency is at least partly on account of the online auction market allowing greater aggregation of supply and demand across multiple spatially separated physical markets. First, the data suggest that vehicles auctioned online sell for prices significantly higher than those sold offline. After controlling for vehicle type and miles driven, the price difference between vehicles sold via online and offline channels is 2.7% (or \$351.79 per vehicle). The data also suggest that the dispersion of prices obtained for vehicles sold is significantly narrower in the online channel than for the offline channel.

These findings may be the result of reduced transaction costs for buyers in the online market. However, as we discuss later in the paper, the price difference observed between vehicles sold via online and offline channels in this data set is greater than one would expect to see from reduced transaction costs alone. For example, in a related study, Garicano and Kaplan (2001) suggest that the online transaction costs savings in a similar setting could range from \$20-\$180.

If inefficiencies present in the offline channel allow intermediaries (car dealers) to exploit arbitrage opportunities across geographies, by reducing these inefficiencies, the online channel may allow the seller to capture a portion of the arbitrage rents. Consistent with the arbitrage explanation, we find that, even while controlling for vehicle types, that there are significant differences in prices obtained for vehicles across locations of physical

auctions and that the flow of vehicles sold between states in the online channel is associated with price differences between states, with vehicles flowing from low cost states (states where vehicles command relatively lower prices) to higher cost states.

2. Relevant Literature and Hypotheses.

2.1. Online vs. Offline Price Levels.

To date, the bulk of work comparing online and traditional prices has examined posted prices and focused on consumer welfare. The results of these studies have been mixed. For example, Brynjolfsson and Smith (2000) examined the “friction free market” hypothesis by comparing traditional and online book and CD sales. They found that the prices for books and CDs sold over the Internet were 9-16% less than identical items sold via traditional channels. Tang and Xing (2001) compared DVD prices of the online branches of traditional retailers and pure Internet retailers. They found that, for similar DVDs, pure Internet retailer prices were \$3.27 or 14% lower prices than the online channels of traditional retailers. Supporting this, Ancarani and Shankar (2002) also found that prices of books and CDs in Italy were lower for online than for offline retailers and Goolsbee (2001) found that online prices for computers were lower than those sold via traditional channels.

However, Clay et al. (2002) found no difference in the prices of online and traditional booksellers. Similarly, Lee and Gosain (2002) found that the prices for old-hit music CDs were lower on the internet but that there was no difference in the online and offline prices for current-hit CDs. In one of the first studies in the area, Bailey (1998) found that online prices were higher for books, CDs and software.

Although conventional wisdom and much of the earlier work in this area suggest that lower search costs online should lead to lower prices, several recent studies suggest that, under certain circumstances, reduced search costs may lead to higher prices and reduced consumer welfare (e.g., Campbell, Ray, & Muhanna, 2005; Lal & Sarvay 1999; and Lee 1994). Lal and Sarvay (1999) showed that under certain conditions use of the Internet may not only lead to higher prices but could also discourage customers from engaging in search. In related work, Lee (1994) noted that lower search costs may allow firms to engage in price matching strategies which could reduce consumers' bargaining power and make buyers worse off. Similarly, recent analytical work by Campbell et al (2005) demonstrated that reduced search costs can facilitate firms' ability to collude resulting in higher prices and reduced consumer welfare.

2.2. Online vs. Offline Auction Characteristics.

Kazumori and McMillan (2005) observe that transaction costs for both buyers and sellers are higher in live auctions than in online auctions. They report that for online auctions, the seller's costs are limited to those of running the web site. However, for live auctions, they note that the auctioneer pays the costs of mounting the pre-sale exhibition and in running the theatrical performance that makes up a live auction. Similarly, for online auction bidders, the costs of participating online are minimal; however, bidders in live auctions must incur travel and other participation costs.

Kazumori and McMillan (2005) also suggest that there are two main differences between online and live auctions. First, they suggest that less information is available to bidders in online auctions. In live auctions, they note that buyers have an independent indication of the quality of the goods for sale, in the form of their own evaluation.

However, they point out that online shoppers are physically unable to inspect products for sale and must rely entirely on pictures and descriptions posted by the seller. They also observe that the fuzziness of pictures on a computer screen further limit an online bidder's information. As a result, they suggest that the information advantage of the sellers may be more pronounced in online auctions than in other settings. This is consistent with Wolf and Muhanna (2006) which found that information asymmetry does affect bid levels in eBay Motors auctions. Given sellers' information advantage in online auctions, Kazumori and McMillan suggest that bidders may worry more about the "winner's curse" and bid lower as a result. Along these lines, Bajari and Hortaçsu (2003) examine data from eBay coin auctions and find evidence of a "winner's curse." Their data suggests that buyers shave their bids by 12 percent due to their uncertainty about the object's worth. However, the setting examined in this study is different from those found in both Kazumori and McMillan and in Wolf and Muhanna (2006). Both of these studies examined retail auctions where bidder experience and trust in sellers significantly affect bidder behavior. Here, we are examining a wholesale market with professional buyers and a trusted seller that offers guarantees and a return policy. As such, the informational advantage of the seller is not expected to affect bidder behavior in this setting.

Overby and Jap (2008) list several difference between online and offline (or collocated) auctions noting that electronic auction markets may have reduced transaction costs, but may also have higher quality uncertainty and risk. They note that physical and electronic markets differ in the manner that the buyers participate in each auction type, the manner in which the products are presented, as well as several market policy factors (i.e.,

the ways in which disputes are resolved, the transaction window and the price discovery methods).

Finally, Kazumori and McMillan (2005) note that the live auction seller must wait until a suitable auction is scheduled, bringing additional costs of delay. Garicano and Kaplan (2001) suggest two important costs of delay are the costs of capital and depreciation. They note that each day an item waits to be auctioned is another day the seller is unable to deploy that capital elsewhere. In addition, they point out that for durable goods (e.g., automobiles) the sale price declines with age. This means that, for many types of goods, each day an item waits to be auctioned its value decreases.

2.3. Online vs. Offline Vehicle Auction Prices.

Previous studies of online and offline vehicle prices (Lee, 1998; Garicano and Kaplan, 2001; and Wolf and Muhanna, 2005) suggest that prices are higher in online markets. In his seminal work comparing online (or click) to traditional (or brick) market mechanisms, Lee (1998) studied the Japanese wholesale market for used cars and tested whether electronic markets lower prices. In Japan, as in the United States, used car dealers typically procure the inventories through wholesale auto auctions. Lee looked at cars sold via AUCNET, an electronic auction, and compared them to cars sold via Japan's 143 traditional auto auctions. Lee found that cars sold through the electronic market, AUCNET, were more expensive than those sold in traditional auto auctions.

In Lee's study, the results appear to be largely driven by quality differences in the vehicles sold. The electronic auction sold newer cars, with lower mileage and the buyer knew the exact condition of the vehicle, while the traditional auctions studied sold older

cars with more miles and questionable quality. Before going on the auction block, AUCNET mechanics inspected and rated every vehicle. The cars in Lee's study were given a ranking between 1 and 10. New cars were ranked as a 10 and cars rated 5 or 6 were deemed worthy to be sold to the customer without additional work. All cars rated lower than 4 were excluded from the electronic auctions. Lee acknowledged the limitations of the study and speculated that the auctioned vehicle prices were influenced by economic factors beyond buyer search costs (and vehicle quality).

Among the factors that Lee believed caused the higher AUCNET prices was the lack of convenience and opportunity costs of attending a traditional auction, the wider selection of vehicles available via AUCNET, and the larger number of bidders that could be accommodated in the electronic auctions. At the time of the study, AUCNET had 4000, or four times the number of bidder seats available for its auctions than its next closest competitor had. Lee (1998) noted that buyer externality implied that benefits realized by individual sellers increases as more buyers joined the bidding. In other words, as the number of bidders increased, the expected price also increased. Lee further noted that AUCNET listed and sold more cars than its competitors.

Wolf and Muhanna's (2006) examination of online and offline prices also found that that vehicles sell on eBay at prices higher than offline. However, because of an important limitation of the data in that study, namely that the prices examined online (eBay) and offline (Kelley Blue Book private party) originated from different mechanisms, and differences in price levels may be influenced by factors other than the location of the transaction, the results should be interpreted cautiously. In a related study, Garicano and Kaplan (2001) looked at pre-owned vehicles sold online to auto dealers via Autodaq.com

and estimated the price that the vehicle would have obtained if purchased in the offline wholesale market finding that online prices were significantly higher than those in the physical world.

Garicano and Kaplan suggested that the higher online prices could be the result of several factors including lower transaction costs. Wolf and Muhanna's (2006) also mentioned several possible explanations for these findings that may also be applicable to this setting. First, perhaps the greater selection of products online make it more likely that buyers find vehicles with make, model, and options that matched their preferences. If this is true, the higher price levels may reflect buyers' willingness to pay for a closer match. In addition, shopping online may require less time and effort than buying offline and the higher prices may reflect customers' value for time savings and ease of use. Another factor is that there are a larger number of online buyers than attend individual offline auctions, so perhaps the higher prices are simply the result of a large number of bidders.

There are several limitations and possible explanations for these findings. First, at least in Lee's study of AUCNET, the results appear to be largely driven by quality differences in the vehicles sold. The electronic auction sold newer cars, with lower mileage and the buyer knew the exact condition of the vehicle, while the traditional auctions studied sold older cars with more miles and questionable quality. Similarly, Overby and Jap (2008) found that in markets with both online and offline channels, that vehicle wholesalers were more likely to offer hard-to-find vehicles and those with lower quality uncertainty online, while those vehicles which were more common or which had greater quality uncertainty were more likely to be offered in offline auctions. Findings from Garicano and Kaplan (2001) and Wolf and Muhanna (2005) are also limited since both use

sales in the physical retail (as opposed to auction) markets (Kelley Blue Book) as the benchmark market.

These limitations notwithstanding, perhaps the greater selection of products online makes it more likely that buyers will find vehicles with make, model, and options that matched their preferences. If this is true, the higher price levels may reflect buyers' willingness to pay for a closer match. In addition, shopping online may require less time and effort than buying offline and the higher prices may reflect customers' value for time savings and ease of use. Since bidders do not need to be physically present during the auction process, online auctions may facilitate longer auctions. As a result, online vehicle prices may be higher due longer auction durations. Another possible factor is that in each of these studies, the number of online auction participants was significantly larger than the number of buyers attending individual the offline auctions, so perhaps the higher prices are simply the result of a large number of bidders.

Finally, prices for online auctioned vehicles may be higher than those auctioned offline due to increased market integration and gains in efficiency. In the offline setting, the search costs required to locate a vehicle that matches the buyer's preferences, travel to the auction site and make a purchase limit the buyer's ability to participate in auctions too far from home. The online market reduces the search costs required for buyers to locate and bid on desirable vehicles. This reduction in search costs is most pronounced for vehicles auctioned at locations outside of the dealer's immediate area. As a result, online markets may lead to increased price levels by facilitating the sale of vehicles to buyers that reside outside of the immediate area of the auction but that have higher valuations for the vehicles.

Considering each of the factors that positively or negatively affect vehicle auction prices, we believe that the increased market integration and gains in efficiency of online auctions coupled with lower buyer transaction costs, greater convenience, increased vehicle selection, and the larger number of bidders will outweigh factors that would drive down the price of the auctioned items (adverse selection on account of the inability to physically assess the quality of the vehicle). As a result, we believe that, in wholesale markets for relatively new vehicles from a reputable seller, we will find that online prices are higher than prices in traditional markets. Thus:

HYPOTHESIS 1. Prices for comparable vehicles will be higher in online auctions than in traditional auctions.

2.4. Price Dispersion.

With the growth of the Internet and electronic commerce, an unprecedented amount of product and price information is now easily accessible to potential buyers. The addition of search engines, infomediaries and shopbots further reduces buyer search costs and makes comparison shopping possible on scales never before imagined. It has been widely anticipated that the readily available price and product information coupled with reduced search costs would cause Internet markets to display pricing consistent with the textbook case of the “law of one price” (Baye, Morgan, & Scholten, 2006).

As a result, Internet price dispersion has been widely investigated. Much of this work has focused on the effects of reduced buyer search costs (e.g., Bakos, 1997; Brynjolfsson & Smith, 2000; and Clay, Krishnan, Wolff, & Fernandes, 2002) in online markets. Economic researchers have long looked at price dispersion in traditional markets

(e.g., Salop & Stiglitz 1982; Sorensen 2000; and Stigler 1961). More recently, researchers have turned their attention to online markets (e.g., Morgan, Zettelmeyer, Silva-Risso, 2001; Pan, Ratchford & Shankar 2003; and Smith, Bailey & Brynjolfsson, 2002). There are several theoretical and empirical studies comparing online and offline markets. However, to date, the results have been mixed.

While most studies have found lower prices in online markets, the empirical findings also seem to indicate that online price dispersion is no less than offline price dispersion (Pan et al. 2003). As with studies of price levels, most work examining online and offline price dispersion has focused on the effects of reduced search costs and examined posted prices. For example, Brynjolfsson and Smith (2000) find lower price dispersion in online CD and book markets, but only when market share is considered. The bulk of remaining research into this area seems to suggest that, contrary to theoretical predictions, price dispersion is as persistent in online markets as it is in traditional markets (e.g., Arnold & Saliba, 2003; Baye et al., 2006; Clay et al.; Clemons, Hann, & Hitt, 2002).

There are competing explanations for the persistence of price dispersion in online markets. One explanation, fueled by the fact that some more recent studies show lower dispersion (e.g., Ellison & Ellison 2001), is that price dispersion is a transitory phenomenon and that dispersion will converge to the law of one price as consumer awareness increases and competition increases. Brown and Goolsbee's (2000) finding of reduced dispersion with increased Internet usage would be consistent with his view. Ratchford, Pan and Shakar (2003a) and Pan et al. (2003) support the idea of Internet dispersion decreasing over time. However, later work by Pan and Shankar (2004) suggests that price dispersion is more permanent.

An alternative view is that price dispersion is a persistent phenomenon and driven by market specific factors (e.g., Baye et al., 2006). Arnold and Saliba (2003) propose a model of persistent price dispersion in equilibrium even when all consumers are perfectly informed about prices charged by all firms. Their examination of the online textbook markets finds that some firms adopt a high-price high-availability strategy while others adopt a low-price low-availability strategy. Finally, Chevalier and Goolsbee (2002) mention that while relatively high prices may be posted on some Internet sites; few or no transactions may be taking place at those relatively high prices. Without quantity data, it is impossible to know.

We believe that the results of previous studies may be, at least partially, driven by the data available. The bulk of previous empirical research examined listed product price instead of transaction price because of the limitations of the data available. However, examining posted prices potentially skews results by including items that will never sell because they are unreasonably priced or products that are not actually available, but intended to lure shoppers to the e-tailer's site. In addition, the varying designs and ease of navigation of e-tailer sites, the return policies, shipping costs, customer service, and several other factors add to firm heterogeneity (Brynjolfsson & Smith, 2000; Pan et al., 2003; Pan et al., 2004). Similarly, trust is a critical factor in online transactions which makes price comparisons across vendors more difficult. Finally, consumer heterogeneity in factors such as search behavior or knowledge of available online vendors or search engines is another difficulty that may affect dispersion (Ratchford, Pan, & Shankar 2003; Varian 1980).

Given the limitations of previously available data, it has been very difficult to isolate the effects of reduced search costs, lower buyer and seller transaction costs, or other factors associated with the Internet from the variation in e-tailer service quality and other market and product factors that affect price dispersion. A convincing comparison of online and traditional market price dispersion would employ a sample of completed sales of heterogeneous products from a single vendor via both channels using a single selling mechanism. We believe that a fresh examination of the issue with a dataset unencumbered by the difficulties mentioned above may yield different results.

When discussing the effects of electronic markets on search costs, previous work has focused on the Internet's ability to facilitate price comparisons. The search costs in this setting are slightly different from those explored in the bulk of previous literature and include the costs required to locate a product (i.e., a vehicle) that closely matches the buyer's preferences and the buyer's costs of participating in the bidding process. As mentioned earlier, in the traditional auction setting, these search costs reduce buyers' ability to participate in vehicles auctions held too far from home and these buyer search costs are lower in the online market than in the traditional market. In addition, online users can also more easily observe the behavior of other market participants. As a result, vehicles sold online may be less likely to be affected by regional market forces and preferences, and may be more likely to be sold at a "nation price." Therefore, we expect to find decreased price dispersion in the online auctions. Specifically, we wish to test the following hypothesis:

HYPOTHESIS 2. Price dispersion for comparable vehicles will be lower in online

auctions than in traditional auctions.

3. Data and Methods

When a customer's auto lease ends, the customer usually has the option of purchasing the leased vehicle or returning it to an authorized dealer, referred to as the grounding dealer in this context. Since the manufacturer, or more accurately, the financial services arm of the manufacturer, retains title to these vehicles, they are prevented by law from reselling the vehicles directly to consumers. As a result, the vehicles are sold to authorized dealers who in turn sell the vehicles to consumers. Typically off-lease vehicles are either sold to the grounding dealer for a fixed price or sold at dealer-only regional auctions. In recent years, off-lease vehicles, have replaced "program vehicles" and trade-ins as a key supply source of late-model used vehicles for auto dealers. In another recent development, a number of auto manufacturers have started to sell their off-lease vehicles via dealer-only online auctions.

To test the above hypotheses, that online prices will be higher and price dispersion will be lower than traditional markets, we examined off-lease auto sales data from both traditional and online auctions. To accomplish this goal, we were given access to several months of auction data from the financial services arm of a large auto manufacturer. The data set includes descriptive information about the vehicles sold, the costs incurred and prices obtained for each vehicle, as well as the location of the sale and buyer information. To control for vehicle fixed effects, a "vehicle type" is defined as a unique combination of model, body type (e.g., convertible, coupe, hatchback, sport utility), doors (e.g., 2 door, 4 door, 4D Ext Cab), trim level, drive train type (e.g., 2WD, 4WD), transmission type

(automatic, manual), cylinders (e.g., 4 Cylinders, 6 Cylinders), displacement (e.g., 3.0 liters, 3.3 liters), and model year. Vehicles with fewer than 50 observations in either market were dropped from the sample. We have chosen to limit the sample to those vehicle types with 50 or more sales in both the online and offline markets to ensure a large sample size while maintaining sufficient degrees of freedom to perform the needed statistical analysis.

To empirically test Hypothesis 1, we performed a regression on the purchase price of the auctioned vehicle. The independent variables were “vehicle type” dummies, vehicle mileage, and an indicator which denotes whether the vehicle was sold online or offline. We identify these unique “vehicle types” by using the first ten digits of the vehicle identification number (VIN). The model is:

$$(1) LN(Price) = \beta_1 * LN(Miles) + \beta_2 * Online + \sum_{i=1}^{121} \beta_{i+2} * VehicleType_i + \varepsilon$$

I performed this analysis for 121 unique vehicles types with 30,533 combined vehicle sales (10,898 offline and 19,635 online).

To empirically test Hypothesis 2, consistent with Sorensen (2000) and Pan et al. (2003), we examined five price dispersion measures: (1) price range, (2) percentage difference (range of price relative to the average price), (3) standard deviation, (4) variance of prices, and (5) coefficient of variation (standard deviation of price relative to the average price). As with Hypothesis 1, we identified unique vehicles by the first ten digits of the vehicle identification number (VIN). We then compared the online and offline means of each measure via paired t-tests. In addition, we also compared each online and offline measure using sign tests and Wilcoxon signed-rank tests. We performed this analysis using the same 30,533 vehicle sales used to test Hypothesis 1.

4. Results

Table 1 (column A) summarizes our testing of Hypothesis 1. The data suggest that even after controlling for vehicle type and mileage, that the online selling price is significantly higher than the selling price for comparable vehicles in the tradition market. Further (columns B and C) suggests that the relationship between vehicle miles and sale price is weaker for vehicles sold online.

{Insert Table 1}

For each of the five measures of price dispersion, Hypothesis 2 is supported. In fact, the results each t-test and every non-parametric test was consistent with the hypothesis that price dispersion for vehicles sold online is lower than the price dispersion for vehicles sold in the traditional market. The mean standard deviation of the sales amount for vehicles sold online was 1223.381, and mean standard deviation for vehicles sold offline was 1468.084. This difference was significant, $t(120) = -10.4879, p < .001$. A sign test ($p < .001$) and a Wilcoxon signed-rank test, ($z = -8.152, p < .001$) also suggest that the standard deviation of the sales amount for vehicles sold online is significantly lower than the standard deviation of the sales amount for vehicles sold in the traditional market.

The mean variance of the sales amount for vehicles sold online was 1674081, and mean variance for vehicles sold offline was 2405847. This difference was significant, $t(120) = -8.5992, p < .001$. A sign test ($p < .001$) and a Wilcoxon signed-rank test ($z = -7.989, p < .001$) also suggest that the variance of the sales amount for vehicles sold online

is significantly lower than the variance of the sales amount for vehicles sold in the traditional market.

The mean percentage difference of the sales amount for vehicles sold online was 0.534121, and mean percentage difference for vehicles sold offline was 0.67549. This difference was significant, $t(120) = -9.8918, p < .001$. A sign test ($p < .001$) and a Wilcoxon signed-rank test ($z = -7.849, p < .001$) also suggest that the percentage difference of the sales amount for vehicles sold online is significantly lower than the percentage difference of the sales amount for vehicles sold in the traditional market.

{Insert Table 2}

The mean price range of the sales amount for vehicles sold online was 6506.612, and mean price range for vehicles sold offline was 7750.413. This difference was significant, $t(120) = -8.0212, p < .001$. A sign test ($p < .001$) and a Wilcoxon signed-rank test ($z = -6.838, p < .001$) also suggest that the price range of the sales amount for vehicles sold online is significantly lower than the price range of the sales amount for vehicles sold in the traditional market.

The mean coefficient of variation of the sales amount for vehicles sold online was 0.1015678, and mean coefficient of variation for vehicles sold offline was 0.127164. This difference was significant, $t(120) = -13.0976, p < .001$. A sign test ($p < .001$) and a Wilcoxon signed-rank test ($z = -8.697, p < .001$) also suggest that the coefficient of variation of the sales amount for vehicles sold online is significantly lower than the coefficient of variation of the sales amount for vehicles sold in the traditional market.

One explanation for higher prices in the online channel is the presence of arbitrage opportunities in the offline channel. If inefficiencies present in the offline channel allow intermediaries the potential to exploit arbitrage opportunities, by reducing these inefficiencies, the online channel may allow the manufacturer to capture a portion of the arbitrage rents. We tested this explanation several ways. First, we performed a simple OLS regression using the 10,851 vehicles from our sample that were auctioned offline and had complete location information. The 47 locations each represent a unique auction location. The data suggest that even while controlling for vehicle type there are significant differences in prices obtained for comparable vehicles across locations. This suggests the possibility that there are unexploited opportunities for arbitrage in the traditional sales channel. Next, we examined the flow of cars between states in the online auction.

{Insert Table 3}

Also supporting this, Table 3, shows that dealers from states with high (state type 3) and medium (state type 2) average prices are net importers of vehicles, while dealers from states with low (state type 1) average prices are net exporters. It is interesting to note that 54% of all vehicles bought by dealers from states with medium (state type 2) prices come from low cost states. By contrast, these same dealers buy relatively very few vehicles from high (state type 1) cost states (<9%).

Next, we utilized a pair of gravity equations to further test whether the flow of vehicles between states is affected by the differences in the prices of vehicles sold in each state. Originally developed by Newton, the gravity equation holds that the attractive force

between two objects is affected by the masses of, and the distance between, the two objects (Head, 2003). The functional form of the gravity equation is commonly employed to study bilateral flows of goods, services and people across regional and international borders (e.g., Tinbergen, 1962; Linneman, 1966; Anderson, 1979; Krugman, Cooper and Srinivas, 1995; McCallum, 1995; and Anderson & Van Wincoop, 2003).

As McCallum (1995) notes, these studies use gravity-type equations to examine the determinants of international trade patterns, including the impact of preferential trade blocs. Trade between any two countries is a function of each country's gross domestic product, the distance between them, and possibly other variables. Further, Anderson and Van Wincoop (2003) note that the gravity equation has been used to infer the effects of institutions such as customs unions, exchange rate mechanisms, ethnic ties, linguistic identity and international borders on bilateral trade flow. To further test whether the flow of vehicles between states is affected by the differences in the prices of vehicles sold in each state, we employed the following gravity models:

$$(2) \quad LN(Flow_{ij}) = \beta_1 * LN(Sales_i) + \beta_2 * LN(Purchases_j) + \beta_3 * LN(PriceDifference_{ij}) + \beta_4 * LN(Distance_{ij}) + \varepsilon$$

$$(3) \quad LN(Flow_{ij}) = \beta_1 * LN(Population_i) + \beta_2 * LN(Population_j) + \beta_3 * LN(PriceDifference_{ij}) + \beta_4 * LN(Distance_{ij}) + \varepsilon$$

In both models, *Flow* is the number of vehicles sold in the online market in state *i* to dealers in state *j*. In model 2, we use *Sales* and *Purchases* as the “masses” in the gravity equation. In model 3, the populations of the buying and selling states are used. In model 2, *Sales* denotes the total number of vehicles sold by dealers in state *i*, and *Purchases* is the total number of vehicles purchased by dealers in states *j*. In model 3, *Population_i* denotes

the population of the state where the vehicle was sold, and $Population_j$ denotes the population of the state where the vehicle was purchased. In both models $PriceDifference$ denotes the difference in the price coefficients for vehicles sold in state i and state j .

A two step process was used to obtain the price differences. First, we performed an OLS regression on the 10,898 offline vehicle sales used to test Hypothesis 1, with the natural log of sales price as the dependent variable and the natural log of vehicle miles and dummies for both the vehicle type and the state where the auction was held as independent variables. The data set examined included offline sales from 35 states. Next, to calculate price differences for each state pair, the resulting state coefficients for the buying states were subtracted from the state coefficient of the selling states. In both models, $Distance$ represents the miles between the population-weighted centroids or “population centers” of states i and j . Each state’s population as well as the location of the population-weighted centroid was obtained from the U.S. Census Bureau’s website¹ and reflect data from the 2000 census.

{Insert Table 4}

Table 4 summarizes the results of the previously specified gravity models. In both models (columns A and B), the coefficients for $PriceDifference$ are negative and significant. Since $PriceDifference$ is essentially a proxy for economic impedance between states (i.e., the inverse of cross-state arbitrage opportunities), these results suggest that trade flow between states is negatively associated with the price-level impedance factor, or in other words,

¹ <http://www.census.gov/geo/www/cenpop/statecenters.txt>

positively associated with arbitrage opportunities. In other words, in the online market, the data suggest that vehicles are flowing from low price states to high price states. In short, the data suggest an arbitrage effect.

In one final test of the effect of the online channel on arbitrage opportunities, we performed a mean revision regression with relative offline price as the dependent variable and relative online price as the independent variable. Relative online and offline prices were obtained by first performing an OLS regression on the same 30,533 vehicle sales used to test Hypothesis 1, with the natural log of sales price as the dependent variable and the natural log of vehicle miles and dummy variables for online, vehicle types and states and an interaction term for online and each state as the independent variables. The data set examined included online and offline sales from 35 states.

{Insert Table 5}

From the results of this regression, the online and offline coefficients relative to the state of Alaska were obtained. From these relative coefficients, online and offline coefficients relative to each of the other 34 states were calculated. Table 5 shows the results of the mean revision regressions. Column A shows the results of the mean revision regression when all 1225 (35 X 35 states) online and offline coefficients are included. Column B shows the results when the diagonal observations involving self-differentials (all of which had zero values) were dropped. In both models, the coefficients on the relative online coefficients are negative and significant, suggesting significant mean

revision and supporting the notion that the range of prices in the online market is smaller than the range of offline prices.

Each of these findings is consistent with the suppositions that online prices converge more closely toward a national price than offline prices and that the online channel may allow the firm to capture at least a portion of the arbitrage rents.

5. Discussion

Our findings suggest that an Internet sales channel does add economic benefit. First, data suggest that price dispersion is narrower in the online channel than offline. For this study, we used five measures of price dispersion, and for each measure, using comparable vehicles, we found less dispersion online than in the offline markets. In addition, we find that the sales price of vehicles sold online is significantly higher than the sales price offline. There are several possible reasons for these findings. Perhaps the greater selection of products online makes it more likely that buyers find vehicles with make, model, and options that match their preferences. If this is true, the higher price levels may reflect buyers' willingness to pay for the closer match. In addition, shopping online may require less time and effort than buying offline and the higher prices may reflect customers' value for time savings and ease of use. Finally, consistent with general auction theory, the higher prices may simply be the result of a larger number of online buyers.

Garicano and Kaplan (2001) suggest that wholesale auto shoppers could save between \$20 and \$180 in transaction costs by purchasing online. This cost represents the

cost of a dealer traveling to the auction site and participating in the bidding. The data in this study suggest that the gap between online and offline prices is greater than that which could be explained by transaction costs alone. For example, Table 1 shows that, after controlling for vehicle type and miles driven, the price difference between vehicles sold online and offline is 2.7% (or \$351.79 per vehicle).

Table 4 summarizes the results of the previously specified gravity models. In both models (columns A and B), the coefficients for *PriceDifference* are negative and significant. Since *PriceDifference* is essentially a proxy for economic impedance between states (i.e., the inverse of cross-state arbitrage opportunities), these results suggest that trade flow between states is negatively associated with the price-level impedance factor, or in other words, positively associated with arbitrage opportunities. In other words, in the online market, the data suggest that vehicles are flowing from low price states to high price states. In short, the data suggest an arbitrage effect.

These findings are consistent with several studies which suggests that technology may reduce arbitrage and facilitate market integration in financial markets. Garbade and Silber (1976) examined the impact of technological innovations on financial markets and found that innovations in communications technology, specifically the domestic telegraph and the trans-Atlantic cable, led to significant and rapid narrowing of inter-market price differentials on the integration of geographically separated markets. Garbade and Silber suggest that these technologies provided opportunities for accelerated search and order execution induced more efficient arbitrage between markets, thereby reducing inter-market price differentials and increasing market integration. Similarly, Kempf and Korn (1996)

examined derivative markets using floor trading and screen (computer) trading systems. They found closer integration in derivative markets with screen trading; results were more pronounced during heavy trading.

6. Conclusion

This paper makes several contributions both to the newly emerging stream of research on Internet channel addition and to the growing stream of research on online price dispersion. This study is the first to compare price dispersion of online and offline auctions. The data suggest that price dispersion is narrower in the online channel than in the offline channel. Next, the data suggest that wholesale vehicles sell for significantly higher prices online than offline. This is significant in that the data examined is free from the quality heterogeneity that drives Lee's results, but the findings are similar.

Subsequently, we use these findings as a springboard to explore the underlying causes of the higher online prices and lower online price dispersion. We are able to show that gap between online and offline prices is greater than one would expect from a reduction in buyer transaction costs alone. Next, we find that there are significant differences in the prices obtained for vehicles sold across locations and that these price differences appear to affect the flow of used vehicles between states. After that, using a gravity model, we show that the flow of vehicles between states is associated with price differences between states, with vehicles flowing from low cost states to higher cost states. This work is the first in the field of information systems to utilize the gravity equation in the statistical analysis. Finally, using mean revision regression with relative online and

relative offline prices by state, we show that the range of online prices is narrower than the range of offline prices. The findings of each of these tests are consistent with the suppositions that online prices converge more toward a national price than offline prices and that the online prices may be higher because the online channel allows the firm to capture a portion of the arbitrage rents.

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APPENDIX

In this setting Price is the sale price of the vehicle. Online denotes whether the vehicle was sold online (1) or offline (0). Miles is the vehicle mileage and a “vehicle type” is defined as a unique combination of model, body type (e.g. convertible, coupe, hatchback, sport utility), doors (e.g. 2 door, 4 door, 4D Ext Cab), trim level, drive train type (e.g. 2WD, 4WD), transmission type (automatic, manual), cylinders (e.g. 4 Cylinders, 6 Cylinders), displacement (e.g. 3.0 liters, 3.3 liters) and model year. Vehicles with fewer than 50 observations in either market were dropped from the sample.

	(A)	(B)	(C)
	Log of price	Log of price	Log of price
Online	0.044	0.027	0.027
	(30.93)**	(24.66)**	(24.05)**
Centered Log of Miles		-0.206	-0.224
		(139.51)**	(94.92)**
Online * Centered Log of Miles			0.030
			(10.13)**
Vehicle Types 1-121	Included	Included	Included
Constant	-0.292	-0.296	-0.296
	(26.02)**	(33.80)**	(33.87)**
Observations	30533	30533	30533
R-squared	0.91	0.95	0.95
Absolute value of t statistics in parentheses			
* significant at 5%; ** significant at 1%			
Table 1. Regression Results: Vehicle Sale Price			

In this setting Price is the sale price of the vehicle. Miles is the vehicle mileage and a “vehicle type” is defined as a unique combination of model, body type (e.g. convertible, coupe, hatchback, sport utility), doors (e.g. 2 door, 4 door, 4D Ext Cab), trim level, drive train type (e.g. 2WD, 4WD), transmission type (automatic, manual), cylinders (e.g. 4 Cylinders, 6 Cylinders), displacement (e.g. 3.0 liters, 3.3 liters) and model year. Vehicles with fewer than 50 observations in either market were dropped from the sample. Location represents the physical location of the vehicle auction.

	Log of Price
Log of Miles	-0.231 (81.29)**
Location 1	-0.173 (3.23)**
Location 2	-0.143 (2.46)*
Location 4	-0.134 (2.21)*
Location 5	-0.143 (2.67)**
Location 6	-0.104 (1.89)
Location 7	-0.190 (3.56)**
Location 8	-0.080 (1.42)
Location 9	-0.101 (1.81)
Location 10	-0.111 (2.07)*
Location 11	-0.092 (1.69)
Location 12	-0.021 (0.37)
Location 13	-0.195 (3.62)**

Table 2. Location Regression Results: Vehicle Sale Amount (continued).

Table 14 (continued).

Location 14	-0.166
	(3.11)**
Location 15	-0.102
	(1.35)
Location 16	0.000
	(.)
Location 17	-0.156
	(2.90)**
Location 18	-0.094
	(1.70)
Location 19	-0.149
	(2.76)**
Location 20	-0.095
	(1.27)
Location 21	-0.145
	(2.72)**
Location 22	-0.046
	(0.81)
Location 23	-0.135
	(2.52)*
Location 24	-0.100
	(1.61)
Location 25	-0.121
	(2.25)*
Location 26	-0.107
	(1.95)
Location 27	-0.152
	(2.85)**
Location 28	-0.151
	(2.82)**
Location 29	-0.093
	(1.74)
Location 30	-0.105
	(1.95)
Location 31	-0.158
	(2.93)**

Table 2. Location Regression Results: Vehicle Sale Amount (continued).

Table 2 (continued).

Location 32	-0.110
	(1.89)
Location 33	-0.124
	(2.31)*
Location 34	-0.149
	(2.76)**
Location 35	-0.122
	(2.28)*
Location 36	-0.104
	(1.92)
Location 37	-0.105
	(1.95)
Location 38	-0.111
	(2.06)*
Location 39	-0.038
	(0.61)
Location 40	-0.084
	(1.04)
Location 41	-0.145
	(2.72)**
Location 42	-0.080
	(1.47)
Location 43	-0.121
	(2.24)*
Location 44	-0.162
	(3.03)**
Location 45	-0.097
	(1.77)
Location 46	-0.129
	(2.39)*
Location 47	-0.040
	(0.66)
Vehicle Type 1-121	Included
Constant	11.173
	(178.57)**
Observations	10851
R-squared	0.93

Absolute value of t statistics in parentheses

* significant at 5%; ** significant at 1%

Sell State	Buy State	#Out of State Sales (OoS)	OoS% of sales for type	Sold In State	Total Sold by Type	% In State
1	1	1605	0.178234314	6396	9005	0.710272
1	2	701	0.077845641	6396	9005	0.710272
1	3	303	0.033647973	6396	9005	0.710272
	total	2609	0.289727929	6396	9005	0.710272
2	1	822	0.170115894	1982	4832	0.410182
2	2	1092	0.225993377	1982	4832	0.410182
2	3	936	0.193708609	1982	4832	0.410182
	total	2850	0.589817881	1982	4832	0.410182
3	1	1678	0.042653787	15454	39340	0.392832
3	2	4422	0.112404677	15454	39340	0.392832
3	3	17786	0.452109812	15454	39340	0.392832
	total	23886	0.607168277	15454	39340	0.392832

Buy State	Sell State	#Out of State Sales (OoS)	OoS % of buys for type	Bought In State	Total Bought by Type	%In State
1	1	1605	0.152842586	6396	10501	0.609085
1	2	822	0.078278259	6396	10501	0.609085
1	3	1678	0.159794305	6396	10501	0.609085
	total	4105	0.390915151	6396	10501	0.609085
2	1	701	0.085519092	1982	8197	0.241796
2	2	1092	0.133219471	1982	8197	0.241796
2	3	4422	0.539465658	1982	8197	0.241796
	total	6215	0.758204221	1982	8197	0.241796
3	1	303	0.008787958	15454	34479	0.448215
3	2	936	0.027146959	15454	34479	0.448215
3	3	17786	0.515850228	15454	34479	0.448215
	total	19025	0.551785145	15454	34479	0.448215

StateType

- 1 High Cost = Top 1/3 by Coeff on State
- 2 Medium Cost = Middle 1/3 by Coeff on State
- 3 Low Cost = Bottom 1/3 by Coeff on State

Table 3. Flow of Vehicles to and from High, Medium and Low Cost States (continued).

Table 15 (continued).

Top of Table

Sell State = the state type (described above) of the state where the selling dealer resides.

Buy State = the state type of the state where the buying dealer resides.

#Out of State Sales (OoS) = number of vehicles that were sold out of state to dealers from this (Sell State) state type to dealers from states with this (Buy State) state type.

OoS% of sales for type = the % of all vehicles sold where sold out of state to dealers from this (Sell State) state type to dealers from states with this (Buy State) state type.

%In State = the % of all vehicles sold by this state type that were sold in-state

Bottom of Table

Buy State = the state type of the state where the buying dealer resides.

Sell State = the state type (described above) of the state where the selling dealer resides.

Out of State Sales (OoS) = number of vehicles purchased by dealers from this (Buy State) state type that were bought out of state from dealers with this (Sell State) state type.

OoS% of sales for type = the % of all vehicles purchased by dealers from this (Buy State) state type that were bought out of state from dealers with this (Sell State) state type.

Total Bought by Type = number of vehicles that dealers from this state type purchased.

%In State = the % of all vehicles purchased by dealers from this state type that were sold in-state

	(A)	(B)
	Log of Flow of Vehicles	Log of Flow of Vehicles
Log of Total Vehicles Sold by Dealers in State	0.347 (14.57)**	
Log of Total Vehicles Purchased by Dealers in State	0.192 (7.36)**	
Log of Difference in Coefficients between Buyer and Seller States	-1.802 (4.37)**	-2.866 (7.59)**
Log of Distance between States	-0.637 (22.30)**	-0.661 (19.01)**
Log of Buying State Population		0.196 (6.07)**
Log of Selling State Population		0.401 (12.53)**
Constant	1.367 (3.96)**	-4.198 (4.98)**
Observations	1225	1225
R-squared	0.58	0.50

Robust t statistics in parentheses
* significant at 5%; ** significant at 1%

Table 4. Gravity Model: Flow of Vehicles Between States

	(A)	(B)
	Relative Offline Coefficient	Relative Offline Coefficient
Relative Online Coefficient	-0.541	-0.541
	(12.26)**	(12.08)**
Constant	0.000	0.000
	(0.00)	(0.00)
Observations	1225	1190
R-squared	0.11	0.11

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%

Table 5. Reversion to Mean Model