Physical and Electronic Wholesale Markets: An Empirical Analysis of Product Sorting and Market Function

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ABSTRACT: Markets can yield significant economic benefits by improving transaction efficiency, but effective design is necessary to achieve these benefits. We compare a physical market to a discrete electronic market in the wholesale used vehicle industry to evaluate how their different designs work for different types of transactions. We find that buyers and sellers balance adverse selection costs and other transaction costs when using the two markets, with the physical market serving as the general exchange and the electronic market serving as a spot market for vehicles with low adverse selection risk. These findings increase our understanding of how sellers and buyers distribute supply and demand between physical and electronic markets in industries in which they coexist. They also increase our understanding of how information technology can improve market function in wholesale environments.

KEY WORDS AND PHRASES: adverse selection, automotive sector, electronic markets, market design, online markets, physical markets, quality sorting, transaction costs.

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The wholesale trade of products such as agricultural commodities, fish, flowers, automobiles, and heavy equipment has traditionally relied on physical collocation of buyers, sellers, and products. Increasingly, transactions for these products are shifting to electronic markets. Electronic markets can reduce transaction costs by lowering the cost of market participation, expanding the pool of potential trading partners, and providing greater convenience [3, 8, 16]. However, they can also create adverse selection costs, particularly when products have "nondigital" attributes that are difficult to represent electronically [2, 7]. We pose two related research questions. First, how do differences in adverse selection costs and other transaction costs influence: (1) how sellers sort products between physical and electronic markets, and (2) how buyers use the two markets to make purchases? Second, what are the roles of physical and electronic markets in wholesale industries in which they coexist? These questions are important because although markets can yield significant economic benefits by improving the efficiency with which buyers and sellers transact, effective market design is necessary if these benefits are to be achieved. Comparing physical and electronic markets allows us to evaluate how their different designs work for different types of transactions and to examine how information technology might be used to improve market function.

Aspects of the first research question have been broached in prior research [10, 14]; we extend those studies by using transaction-level data from both a physical and an electronic market to conduct a more detailed analysis of product sorting in the presence of adverse selection risk than has previously been reported. Importantly, many of our results differ from those of prior research, perhaps because of the granularity of our data. The second question has received relatively little direct analysis, despite its usefulness for considering the effectiveness of the two market types for different types of transactions. Some prior studies in this stream have offered suppositions for the role of the two markets, but they stop short of conducting the in-depth analysis necessary to address the second question directly, perhaps due to data limitations.

We study our research questions using transaction data from a physical market and a parallel electronic market in the U.S. wholesale used vehicle industry. Used car dealers use these markets to source used vehicles for their retail lots and to sell unwanted used vehicles to other dealers. This context is well-suited for our research questions for the following reasons. First, the electronic market eliminates the transaction costs associated with collocation in the physical market but may create adverse selection costs. For example, buyers and sellers can use the electronic market to transact with each other with the click of a mouse, thereby reducing transaction costs for both parties. However, the uncertain quality of vehicles in the electronic market may create adverse selection costs that may offset the reduction in other transaction costs. Second, each vehicle in our data is uniquely identified by its vehicle identification number (VIN), which allows us to track how vehicles flow between the physical and electronic markets as they are being sold. Observing this flow reveals dynamics in how sellers (and buyers) use physical and electronic markets that have not heretofore been documented and that help to delineate the role of each market.

Our results indicate that sellers tend to offer relatively new vehicles in the electronic market, and they tend to offer older vehicles in the physical market because of significant adverse selection costs for such vehicles in the electronic market. Sellers set premium "Buy Now" (i.e., fixed) prices for most of the (relatively new) vehicles they offer in the electronic market. Few vehicles sell in the electronic market (partly due to the premium "Buy Now" prices), and most are later shifted to the physical market, where they sell at auction for the "market" price. As a result, the physical market has a mix of both newer and older vehicles. Sellers are willing to trade off low liquidity in the electronic market for the potential of premium prices because the cost of offering a vehicle electronically is negligible and the physical market serves as a backup option. However, buyers sometimes pay the premiums for relatively new vehicles in the electronic market. We attribute this to the immediacy of the "Buy Now" option, which allows buyers to buy a vehicle at any time without the risk of losing it at auction. Effectively, buyers leverage the convenience and accessibility of the electronic market as a source of "virtual" inventory to fulfill unanticipated retail demand, but only for relatively new vehicles for which adverse selection risk is minimal. Overall, our results indicate that the electronic market functions primarily as a "spot" market while the physical market serves as the general exchange.

Although our analysis is specific to the wholesale used vehicle industry, our conclusions can be extended to other industries. For example, the trade-off between higher adverse selection costs and lower transaction costs in the electronic market is representative of that found in other industries (e.g., [7, 14]). Also, sellers in other industries may use the incumbent physical market as a "fallback" option that enables them to experiment with aggressive pricing strategies in emerging electronic markets, as they do in this industry.

Literature Review

Adverse Selection and Product Sorting in Physical and Electronic Markets

Our first research question involves how differences in adverse selection costs and other transaction costs influence how sellers sort products between physical and electronic markets. In this section, we review the relevant literature on adverse selection costs and product sorting.

Akerlof [1] described how information asymmetry between sellers and buyers can lead to adverse selection and potentially market failure. He illustrated his theory through the used car or "lemons" market, in which some aspects of a used car's quality are *observable* to both the buyers and sellers, while others are *hidden* from buyers but known (at least partially) to sellers. Because buyers are uncertain about the *hidden* quality of the cars, they pay an average price based on the expected hidden quality of cars in the market. Sellers who believe that their vehicles' true value (based on their more informed assessment of *hidden* quality) is less than the average price will offer their cars in the market to receive an average price for a below average vehicle. Sellers who believe that their vehicles' true value is greater than the average price will not offer their cars in the market. Buyers will recognize this and will lower the average price they are willing to pay. The cycle will continue until only an "adverse selection" of "lemons" remains. At the extreme, adverse selection leads to market failure in which no trade occurs. Akerlof [1] recognized that mechanisms exist to prevent adverse selection from causing market failure. Examples of such mechanisms that have been studied in information systems and economics include quality attestations and guarantees [6, 18, 20, 21], product sampling [13, 22], and signals of unobservable hidden quality such as a seller's brand, reputation, or social relationships [4, 19, 23, 27]. In particular, the prospect of damaging their brand or reputation provides a disincentive for sellers to exploit their information advantage over buyers by attempting to obtain high-quality prices for low-quality products [11].

Information asymmetry between sellers and buyers may be starker in some market environments than others, leading to differences in the likelihood of adverse selection. Prior research has tested for adverse selection by comparing different market environments, employing either a direct or an indirect test. *Direct tests* evaluate whether the quality of products traded in a market is lower than what would be expected if all participants were perfectly informed about product quality. For example, Jin and Kato [14] compared the quality of ungraded baseball cards purchased at physical stores to those purchased on eBay by sending them to a quality-grading expert. They found that average card quality on eBay was lower, which they attributed to buyers on eBay being less informed about card quality than buyers at physical stores. Direct tests require that the researcher have information about product quality that is not available to buyers at the time of purchase.[1] *Indirect tests* infer the existence of adverse selection based on price discounts; these discounts are referred to as *adverse selection costs* [7, 10]. For example, Dewan and Hsu [7] and Garicano and Kaplan [10] compared prices between a market with information asymmetry and one with more perfect information to test for adverse selection costs. Because indirect tests do not require that researchers possess information that buyers also do not have, they are easier to implement than direct tests. As described below, we test for adverse selection costs using an indirect test that has precedence in the literature [10, 11, 30].

Related Research

There are a few prior studies that are particularly relevant to our study, many of which share our empirical context of the wholesale used vehicle industry. Genesove [11] focused on the traditional physical market in this industry. He conducted an indirect test of adverse selection costs by comparing the prices of used vehicles sold in the market by new car dealers to those sold by used car dealers. Genesove theorized that the latter group would incur adverse selection costs (i.e., they would receive lower prices) because buyers would be concerned that these dealers would sell used vehicles of low hidden quality in the wholesale market, reserving their better used vehicles for the retail market. He found weak evidence to that effect. Garicano and Kaplan [10] conducted an indirect test of adverse selection costs by comparing the prices of vehicles sold in the electronic market Autodaq (now part of ADESA) to the vehicles' book values. They found no evidence of adverse selection on Autodaq, which they attributed to Autodaq's quality screening procedures that prevented "lemons" from being offered. There were no such institutional constraints on which vehicles could be offered in the electronic market in our context, allowing us to conduct a purer test for adverse selection. Lee [16] compared Aucnet, which is an electronic market in Japan, to the physical market in Japan. Although he did not test for adverse selection, he concluded that vehicle quality was higher in Aucnet, largely because Aucnet disallowed listings for vehicles of suspect quality. He also noted the low costs of participation for buyers in Aucnet versus the physical market. Overby and Jap [25] examined quality sorting across physical and electronic channels available within a single physical market, rather than across separate physical and electronic markets. They concluded that vehicles of predictable quality were traded using the electronic channel; vehicles of unpredictable quality were traded using the physical channel. Although not set in the wholesale market, Lewis [17] and Wolf and Muhanna [30] studied adverse selection using data from eBay Motors. Wolf and Muhanna found evidence (through an indirect test) of adverse selection costs on eBay Motors for older vehicles with higher mileage, while Lewis concluded that sellers' online disclosures can mitigate adverse selection concerns.

As detailed below, we extend the research in this stream by examining adverse selection costs and other transaction costs in both a physical and an electronic market and by investigating multiple sources of adverse selection risk (the seller's type, the nature of the product, and the characteristics of the electronic market). Many of our results differ from prior research, perhaps due to the granularity of our data. We also examine not only the stock of vehicles available in each market at a given time but also the flow of vehicles between markets over time (via the Vehicle Identification Number), which reveals dynamics that have not previously been examined.

The Role of Physical and Electronic Markets

Our second research question involves examining the roles of physical and electronic markets in industries in which they coexist. Analyzing this can shed light on what type of transactions are best suited for each market and lead to insights into market design and operation. Prior literature suggests multiple possibilities for the role of each market, but we are unaware of prior studies that have systematically considered alternative possibilities to identify the role of each market in wholesale trading environments, as we do in the present study.

First, the role of the two markets might be defined by products' observable quality. In this scenario, observably high-quality products trade in one market, while observably low-quality products trade in the other. For example, Garicano and Kaplan [10] and Lee [16] concluded that vehicles' observable quality was higher in the electronic markets they studied than in the corresponding physical markets, largely because the electronic market makers only allowed vehicles of sufficiently high observable quality to be listed, thereby relegating lower-quality vehicles to the physical market. Second, the role of the two markets might be defined by product supply. In this scenario, common products sell in one market while rare products sell in the other. Research on the "long tail" of electronic commerce has shown that the electronic market is often used for trading rare products, while the physical market is used for more common products [5, 12]. Third, the role of the two markets might be defined by the life cycle of the product. In this scenario, one market serves as an overflow channel to dispose of products that are unsold in the other market. For example, Wood et al. [31] examined strategies for retailers to liquidate excess inventory from their physical stores through electronic auctions, and Banker et al. [3] found that traders use the electronic market to sell excess coffee beans. Fourth, the role of the two markets might be defined by how buyers use them to acquire inventory. In this scenario, one market serves as the main source of inventory while the other market functions as a spot market for unanticipated inventory needs. In many cases, the literature on spot markets describes a procurement process in which an electronic spot market is used to satisfy unanticipated needs while a separate (often physical) market is the primary exchange [24, 32].

Empirical Context and Data

The empirical context in which we examine our research questions is the U.S. wholesale used vehicle market, which is a business-to-business market in which buyers and sellers trade used vehicles. Buyers are used car dealers who purchase inventory for their retail lots. Sellers are of two types: (1) used car dealers, and (2) firms that have fleets of vehicles, including rental car firms (that sell vehicles retired from rental service) and leasing firms (that sell vehicles whose lease has expired). We refer to the former as "dealer sellers" and to the latter as "commercial sellers." A used car dealer will sell a vehicle in the wholesale market if he cannot (or chooses not to) sell in the retail market. In this case, the dealer sells the vehicle wholesale to another dealer. Commercial sellers sell in the wholesale market because many lack retail sales outlets and because the wholesale market is a liquid environment for quickly selling large numbers of vehicles. More than 7 million vehicles are sold in the market each year (National Auto Auction Association; www.naaa.com/pdfs/2013AnnualReview.pdf, p. 52).

This market has traditionally operated as a physical market: Buyers, sellers, and vehicles are collocated at physical facilities located throughout the country. At these facilities, vehicles are auctioned one at a time by a human auctioneer who solicits bids via an ascending auction. Over the past several years, the market has introduced electronic trading mechanisms. One mechanism is the *webcast channel,* by which the live auctions occurring at the physical market facilities are streamed via the Internet [25]. This channel allows electronic access to the physical market and is not a "true" electronic market. Another mechanism is a "true" discrete electronic market created as an alternative to the physical market [10, 16, 28]. In this paper, we compare the physical market to the discrete electronic market, which operates similarly to eBay. Sellers list vehicles in the electronic market by uploading descriptions, photographs, and (sometimes) a condition report describing vehicle options, tire condition, and cosmetic damage. The price mechanisms differ between the physical and electronic

Table 1. Summary Statistics for Vehicles Offered and Sold by Seller Type and Market

	Dealer sellers		Commercial sellers	
	Physical market	Electronic market	Physical market	Electronic market
	Vehicles offered			
Vehicle age (years)	6.34	3.84	2.94	1.99
	(3.98)	(2.75)	(2.71)	(1.54)
Mileage	85,690	48,697	44,673	29,932
	(52,155)	(35,119)	(39,259)	(19,671)
Number of vehicles offered	4,533,599	170,161	3,131,156	343,768
	Vehicles sold			
Vehicle age (years)	6.47	3.86	2.96	1.96
	(3.82)	(2.65)	(2.54)	(1.35)
Mileage	84,634	48,636	43,565	28,531
	(48,121)	(36,314)	(36,286)	(14,584)
Number of vehicles sold	2,013,811	13,462	2,140,390	46,239
Number of vehicles sold via auction	2,013,811	486	2,140,390	9,102
Number of vehicles sold/number of vehicles offered	0.44	0.08	0.68	0.13

Notes: Means and standard deviations (in parentheses) shown for Vehicle age and Mileage. *t*-tests indicate that Vehicle age and Mileage are statistically different between the physical and electronic markets ($p < 0.001$) for both dealer sellers and commercial sellers. This is true regardless of whether the analysis is done for vehicles offered or vehicles sold.

markets. All prices in the physical market are determined via an ascending auction, as noted above. Prices in the electronic market are determined either via an ascending auction in which buyers place bids over a pre-set time period (e.g., 1–3 days) or via a fixed “Buy Now” price posted by the seller.

Data were provided by an automotive auction firm that operates multiple physical market facilities, the webcast channel, and the discrete electronic market described above. The data consist of 8,178,684 vehicle offerings from December 2006 to October 2007, 7,664,755 (93.7 percent) of which were offered in the physical market and 513,929 (6.3 percent) of which were offered in the electronic market. There are 5,393,825 distinct vehicles in the sample, meaning that each vehicle was offered 1.52 times on average. We excluded from the sample vehicles for which mileage exceeded 500,000 or had model years prior to 1979. We present summary statistics in Table 1. Table 2 describes the variables in the data.

Table 2. Variables in the Data

Variable	Description
SellerID	Unique identifier of the vehicle's seller.
DealerSeller	Indicator variable set to 1 if the vehicle was offered by a dealer seller and 0 otherwise.
Electronic	Indicator variable set to 1 if the vehicle was offered in the electronic market and 0 otherwise.
DateOffered	Date the vehicle was offered.
Sold	Indicator variable set to 1 if the vehicle was sold and 0 otherwise.
VIN	Vehicle Identification Number of the vehicle.
Model	Make and model of the vehicle (e.g., Ford Taurus).
Mileage	Odometer reading of the vehicle.
VehicleYear	Model year of the vehicle.
VehicleAge	Date the vehicle was offered minus January 1 of the vehicle's model year. May be negative, e.g., if a 2008 model year vehicle was offered in 2007.
ConditionReport	Indicator variable set to 1 if the vehicle had a condition report describing vehicle options, tire condition, and cosmetic damage and 0 otherwise.
Grade	0–5 ordinal grade representing the overall condition of a vehicle as recorded in the condition report. Higher numbers represent better overall condition.
VehicleSupply	Number of vehicles of the same year, make, and model in the data.
FacilityID	Unique identifier for the market facility at which the vehicle was offered.
FacilityZip	Zip code of the market facility.
DealerSellerZip	Zip code of the dealer seller offering a vehicle. Recorded for electronic market transactions only.
BuyNowPrice	Buy Now price of the vehicle in the electronic market, if one was offered.
BuyNowPurchase	Indicator variable set to 1 if the vehicle was purchased via the Buy Now option in the electronic market and 0 otherwise. Coded only for vehicles sold in the electronic market.
Price	Transaction price for the vehicle.
Valuation	The vehicle's estimated wholesale market value based on year, make, model, and mileage; calculated by the firm that provided the data. Not recorded for vehicles offered in the physical market that did not sell.
BuyerID	Unique identifier of the vehicle's buyer.
BuyerZip	Zip code of the buyer.

Key Characteristics of the Empirical Setting

Several features of the empirical setting make it appropriate for studying our dual research questions about: (1) how adverse selection costs and other transaction costs influence the use of physical and electronic markets, and (2) the roles of the two markets when they coexist.

Observability of Vehicle Flow Between Markets

One of the novel features of our data is that we are able to observe how each individual vehicle flows between the physical and electronic markets. Although prior research has examined how sellers sort products of uncertain quality between physical and electronic markets [14], it has examined only the *stock* of products in each market at a given time, thereby ignoring how products *flow* between markets over time. Prior researchers have ignored product flow because they have lacked access to a unique, product-level identifier suitable for tracking flow. We overcome this in our context because each vehicle is uniquely identified by its VIN. We used the *VIN*, *SellerID*, *DateOffered*, and *Electronic* variables (see Table 2) to determine the flow of each vehicle. We identified the first time each vehicle was offered by a given seller and recorded the market in which the seller offered it. If the vehicle did not sell upon its initial offering, we recorded the market in which the seller offered it next.[2] We continued this until either the vehicle sold or it disappeared from the sample.[3]

Quality Uncertainty

The wholesale used vehicle industry is an appropriate context for our analysis of adverse selection costs because the products traded are of uncertain quality, particularly with respect to their *hidden* quality. We justify this as follows. There is no uncertainty about the *observable* aspects of vehicle quality, including a vehicle's year/make/model/trim (e.g., 2007 Ford Focus ZX3 S), mileage, color, and options. Other observable quality attributes such as tire tread depth and whether the vehicle has been repainted can be discerned via physical inspection or by reading a vehicle's condition report. By contrast, there may be significant uncertainty about *hidden* quality attributes such as those related to a vehicle's mechanical condition, including whether the vehicle's engine has been consistently serviced and whether parts such as the timing belt are likely to fail. These hidden quality attributes are observable only with significant effort, which may include lifting the vehicle into the air and/or disassembling parts of the vehicle, neither of which is possible once a vehicle is offered for sale in the wholesale market. These hidden quality attributes are also not described on a vehicle's condition report.

Information Asymmetry

Another reason why the wholesale used vehicle industry is appropriate for our analysis is that sellers have more information about a vehicle's true quality—which consists of both observable and hidden quality—than do buyers [10, 11]. Buyers can diagnose quality by physically inspecting the vehicle at the market facility, by driving it in the parking lot at the market facility (if allowed at that facility), and by reading the vehicle's condition report. They can also check a vehicle's history via the National Motor Vehicle Title Information System (www.vehiclehistory.gov) or via a vehicle history reporting service such as Carfax, although none of these contain much information about a vehicle's hidden quality.[4] Sellers have the same information sources, but they also have access to the vehicle before it enters the wholesale market. This gives sellers the opportunity to conduct a more rigorous inspection, which may include lifting the vehicle or disassembling some elements. Sellers may also have information about the vehicle's history that buyers do not have, including how it has been maintained. This is particularly true for commercial sellers such as rental car firms that regularly maintain the vehicles in their fleets. In these cases, the seller will have access to the detailed maintenance history of the vehicle, while the buyer will not. Although sellers may not reference this information for every vehicle, on average, sellers will have an information advantage.

Commercial Sellers and Dealer Sellers

Another benefit of the empirical context is that there are two types of sellers: commercial sellers and dealer sellers. These have important differences that we exploit in our analysis, including (1) which vehicles they sell in the wholesale market, (2) their incentives for developing and maintaining a good reputation/brand in the wholesale market, and (3) where they store vehicles while offering them in the wholesale market.

First, dealer sellers operate retail lots, and so they can choose which vehicles to sell in the retail market and which to sell in the wholesale market. By contrast, commercial sellers lack retail lots and (generally) sell their entire fleet of vehicles in the wholesale market. The flexibility for dealer sellers to sort vehicles between the retail and wholesale markets creates uncertainty about the quality of the vehicles they offer in the wholesale market, which we return to in the next section.

Second, as discussed above, sellers who have reputations to uphold and/or brand names to protect will be less likely to exploit their information advantage, thereby limiting adverse selection risk to buyers. We argue that reputation matters more for commercial sellers than for dealer sellers because the former have more to lose if they develop a reputation for exploiting wholesale buyers. This is because the wholesale market is commercial sellers' main (and sometimes only) channel for selling vehicles. By contrast, dealer sellers have the option to sell in the retail market if they develop a bad reputation in the wholesale market. Similarly, commercial sellers are typically higher-volume sellers in the wholesale market than are dealer sellers, and many are nationally recognized brands such as Hertz and Avis. As such, they should be less likely to attempt to exploit buyers for fear of damaging their brands. We return to this in the next section.

Third, dealers generally store their vehicles at their retail lots. If a dealer chooses to offer a vehicle in the *electronic* wholesale market, then the vehicle typically remains at his retail lot. If a dealer chooses to offer a vehicle in the *physical* wholesale market, then he transports the vehicle to a physical market facility. If the vehicle does not sell, then he can transport it back to his retail lot. It is important to recognize that dealers routinely transport vehicles back to their retail lots; they do this for every vehicle they purchase in the wholesale market. This means that there is little need for dealer sellers to "dump" vehicles at a discount simply because they brought them to a physical facility. Commercial sellers generally store the vehicles they are offering in the wholesale market at the physical market facilities, which are equipped to store a large volume of vehicles securely. This is popular among commercial sellers because they often lack secure facilities that they can devote to the storage of vehicles that they are offering in the wholesale market. This means that many of the vehicles that commercial sellers offer in the electronic market are actually located at a physical market facility (or are en route to a physical market facility).

Hypothesis Development

In this section, we draw upon theory and prior literature about adverse selection costs and other transaction costs as well as diffusion theory to develop hypotheses about how different sources of uncertainty create adverse selection costs (H1) and how this influences how sellers sort vehicles between markets (H2 and H3). We also consider how sellers set "Buy Now" prices in the electronic market (H4).

Adverse Selection Costs

As discussed above, both buyers and sellers have imperfect information about vehicles' actual quality, although sellers have better information than do buyers. Prior research [2, 7, 10, 30] has argued that if there is information asymmetry about product quality, then it will be more acute in electronic markets where physical product inspection is unavailable. Consistent with this, we argue that the seller's information advantage in our context will be greater in the electronic market than in the physical market. This is because many of the methods available for diagnosing quality require physical access to the vehicle, including touching it, smelling it, driving it, and so on. These methods are not available to buyers when using the electronic market, whereas they are always available to sellers because sellers have physical possession of the vehicles. Furthermore, the seller's information advantage in the electronic market will increase with vehicle age and mileage for the following reason. As discussed above, vehicle quality can be decomposed into *observable* quality and *hidden* quality. The average hidden quality of vehicles—which is a function of unobserved mechanical condition—declines with age and mileage because wear and tear accumulates and components begin to fail. Furthermore, the variability of hidden quality *increases* with age and mileage because there are more hidden quality-related issues that accumulate with vehicle use that the owner may or may not have addressed. Thus, older (newer) vehicles will have relatively low (high) average hidden quality and relatively high (low) variability of hidden quality. As the variability of a vehicle's hidden quality increases, so does the likelihood that the seller has more information about the vehicle's hidden quality than does the buyer.

Information asymmetry, by itself, does not necessarily lead to adverse selection risk. The reason that there is adverse selection risk in our context is because sellers can sort vehicles between the physical and electronic markets. This will cause buyers to suspect that sellers will offer vehicles of below-average hidden quality in the electronic market—where their defects are hard to observe—and reserve the rest for the physical market. The basic adverse selection model predicts that this suspicion (even if unfounded) will cause buyers to discount what they pay in the electronic market, as long as there is a meaningful difference between a below-average and an above-average hidden quality vehicle [1]. This depends on the variability of the vehicle's hidden quality, which depends on vehicle age and mileage. Thus, it follows that buyers will apply discounts in the electronic market to older vehicles with more mileage, but not necessarily to newer vehicles for which the variability of hidden quality is minimal. These discounts are referred to as "adverse selection costs" [7]. Evidence of adverse selection costs does not necessarily mean that sellers' vehicles in the electronic market are *actually* of below-average hidden quality. This is unobserved, both to the buyers and to us. Instead, it means that buyers *believe* that sellers may be sorting their vehicles in this way, such that they react by reducing their willingness to pay. Thus, we are testing for adverse selection costs (an *indirect* test), rather than for adverse selection per se (a *direct* test), which is consistent with prior research [10, 11, 30].

Hypothesis 1a: There are adverse selection costs in the electronic market that are negligible for newer vehicles but that increase with vehicle age and mileage.

As alluded to above, adverse selection costs should be greater for vehicles sold by dealer sellers than for those sold by commercial sellers. First, dealer sellers select which vehicles to wholesale and which to retail, while commercial sellers (generally) wholesale all their vehicles. As a result, dealer sellers have the ability to offer only vehicles of below-average hidden quality in the wholesale market (reserving the rest for the retail market), whereas commercial sellers do not. The *potential* for dealer sellers to behave this way increases the adverse selection risk for buyers. Second, dealer sellers have less incentive to maintain their reputation in the wholesale market than do commercial sellers. Thus, buyers will be more concerned about dealer sellers trying to exploit their information advantage than commercial sellers, thereby increasing the adverse selection risk when buying from dealer sellers.

Hypothesis 1b: The adverse selection costs in the electronic market will be more pronounced for vehicles offered by dealer sellers than for those offered by commercial sellers.

The differences between dealer sellers and commercial sellers may also create adverse selection costs for vehicles sold by dealer sellers in the *physical* market. These costs should be lower in the physical market than in the electronic market given the ability for buyers to physically inspect vehicles in the physical market. However, they may still exist, particularly for older vehicles for which there is a nontrivial amount of uncertainty regarding vehicles' hidden quality.

Hypothesis 1c: There are adverse selection costs for vehicles sold by dealer sellers in the physical market that are negligible for relatively new vehicles but that increase with vehicle age and mileage.

H1a–H1c suggest an ordering of adverse selection costs across the seller type/market combinations. Adverse selection costs should be highest for dealer sellers in the electronic market, lowest for commercial sellers in the physical market, and lie in between these two extremes for commercial sellers in the electronic market and for dealer sellers in the physical market. The ordering of these last two is a priori ambiguous, because it depends on whether the uncertainty associated with dealer sellers outweighs the uncertainty associated with the electronic market, which we explore empirically.

Sorting Between the Physical and Electronic Markets: Stock and Flow

Vehicle Stock

The cost for sellers to list products electronically is negligible [3, 8]. This is because creating an electronic listing is simply a matter of data entry, much of which can be automated. However, sellers may face adverse selection costs in the electronic market, and they must balance these costs against the lower listing costs when sorting vehicles between the two markets. While the listing costs of offering a vehicle electronically are essentially fixed, the associated adverse selection costs should increase with vehicle age and mileage and should be higher for dealer sellers than for commercial sellers (as argued above). As a result, adverse selection costs in the electronic market may outweigh the listing cost savings for (1) older vehicles with higher mileage and (2) for vehicles offered by dealer sellers. This suggests that (1) sellers will be more likely to use the electronic market for newer vehicles with lower mileage for which adverse selection costs are not a significant issue, and (2) dealer sellers will be less likely to use the electronic market than commercial sellers.

> *Hypothesis 2a: Average vehicle age and mileage are lower in the electronic market than in the physical market.*
>
> *Hypothesis 2b: Dealer sellers offer a lower percentage of vehicles in the electronic market than do commercial sellers.*

Vehicle Flow

A seller might offer a vehicle initially in the electronic market and then shift it to the physical market if it does not sell (or vice versa). When a seller offers a vehicle in both markets in this way, we expect her to offer the vehicle in the electronic market first. This is because a seller can offer a vehicle electronically at minimal cost (because listing costs are negligible) before it can be transported and made available at a physical facility.[5] Furthermore, trading has historically occurred in the physical market; trading in the electronic market is relatively new. As a result, most of the trading is likely to continue to occur in the physical market until the electronic market becomes widely adopted, which may take years [26].[6] This suggests that although sellers may *offer* vehicles in the electronic market, many of these vehicles are likely to *sell* in the physical market, which makes it more likely that vehicles will flow from the electronic market to the physical market than vice versa.

Hypothesis 3a: When a vehicle is offered in both markets, it is more likely to be offered in the electronic market first.

Hypothesis 3b: When a vehicle is offered in both markets, it is more likely to sell in the physical market.

Buy Now Prices in the Electronic Market

Two important differences between the physical and electronic markets are that the electronic market is always open and permits posted price transactions. This allows buyers—who are used car dealers—to use the electronic market as a source of virtual inventory [28]. For example, if a retail customer requests a vehicle that a dealer does not have, the dealer can search the electronic market for that vehicle and purchase it immediately for the posted Buy Now price.[7] Sellers recognize the value of the electronic market for this purpose, and we posit that they will attempt to extract some of this value by posting Buy Now prices that are above market value. Also, the physical market represents a backup option for sellers if vehicles do not sell in the electronic market. As such, sellers may be willing to trade off a low likelihood of selling a vehicle in the electronic market for the potential of a premium price because they can always shift unsold vehicles to the physical market where they will fetch the "market" price.

Hypothesis 4: Sellers post Buy Now prices above market value in the electronic market.

It is important to point out that there is no incompatibility between H1a, H1b, and H4. Adverse selection costs can exist in the electronic market (H1a and H1b) even if sellers are posting premium Buy Now prices (H4), partly because many of the transactions in the electronic market do not occur via the Buy Now mechanism. We discuss this in more detail below.

Analysis and Results

Testing H1: Adverse Selection Costs

We tested H1 using the indirect test of adverse selection costs used in prior research in economics and information systems [10, 11, 30]. Equation (1) shows the regression specification:

$$\begin{aligned} Price = {} & \beta_0 + \beta_1{*}MileageAge + \beta_2{*}Valuation + \beta_3{*}VehicleSupply \\ & + \Sigma^5_{g=0}\beta_{4,g}{*}Grade(g) + \beta_5{*}DealerSeller + \beta_6{*}DealerSeller{*}MileageAge \\ & + \beta_7{*}DealerSeller{*}Valuation + \beta_8{*}DealerSeller{*}VehicleSupply \\ & + \Sigma^5_{g=0}\beta_{9,g}{*}DealerSeller{*}Grade(g) + \varepsilon. \end{aligned} \tag{1}$$

Price, *DealerSeller*, *Valuation*, and *VehicleSupply* are defined in Table 2. Because a vehicle's age and its mileage are highly correlated ($\rho = 0.76$), including them both in the regression would lead to parameter instability due to multicollinearity. To address this, we collapsed vehicle age and mileage into a single score, *MileageAge*, which is the score of the first component extracted from a principal components analysis on these variables.[8] The first component explains 86.9 percent of the variance of these two variables. *Grade*(*g*) are a series of dummy variables for the 0–5 ordinal condition grades listed in a vehicle's condition report, if the vehicle has a condition report.[9]

The intuition behind the indirect test of adverse selection costs is to compare each vehicle's price to a reference price that accounts for observable vehicle characteristics, including vehicle age, make, model, and mileage. *Valuation* represents the reference price in our case (see Table 2). If vehicles sell for their reference price, this will be fully absorbed by *Valuation* in Equation (1), such that the *MileageAge* coefficient will be nonsignificant. However, if vehicles sell for below their reference price, and increasingly so at higher levels of mileage and age, then the *MileageAge* coefficient will be significant and negative. In the empirical adverse selection literature [10, 11, 30], these discounts are attributed to concerns about hidden quality and are considered to be adverse selection costs. Because H1 posits differing levels of adverse selection costs for the different seller type/market combinations, we can test H1a, H1b, and H1c by comparing the *MileageAge* coefficients and marginal effects across the combinations.

We tested H1a and H1b by estimating Equation (1) using the vehicles sold in the electronic market in which the price was determined by auction. We tested H1c by estimating Equation (1) using the vehicles sold in the physical market (where all prices are determined by auction). We restricted the analysis to auction transactions because a necessary condition when testing for adverse selection costs is that prices be determined by the willingness to pay of the less informed party (the buyer, in our case) (see [11, 29]). Table 3 presents summary statistics for the variables included in the regressions. Table 4 presents the regression results. Columns 1 and 2 (3 and 4) of Table 4 show the results estimated using the electronic (physical) market transactions. Columns 1 and 3 show the results without the *DealerSeller* interaction terms shown in Equation (1). Table 5 reformats the results for the *MileageAge* coefficients and shows marginal effects to emphasize how they vary across the seller type/market combinations. The *MileageAge* coefficients listed in Table 5 are drawn from columns 2 and 4 of Table 4. For example, the *MileageAge* coefficients for commercial sellers and dealer sellers in the electronic market are β_1 and $\beta_1 + \beta_6$, respectively, from column 2 of Table 4.[10]

As shown in Tables 4 and 5, the *MileageAge* coefficient for dealer sellers in the electronic market is negative and significant ($\beta_1 + \beta_6 = -602.25$, $p < 0.001$), as is the *MileageAge* coefficient for commercial sellers in the electronic market ($\beta_1 = -434.11$, $p < 0.001$). This provides evidence of adverse selection costs in the electronic market that increase with mileage and age, supporting H1a. However, although β_6 is negative, it is not statistically different from zero. Thus, we have no statistical evidence that adverse selection costs are greater for dealer sellers than for commercial sellers in the electronic market, and thereby no statistical support for H1b. This may be because the adverse selection costs of the electronic market exceed those of seller type, making it difficult to separately identify the smaller effect of seller type. It may also be that the number of auction transactions for dealer sellers in the electronic market ($n = 486$; see Table 1) is too low to be able to identify a statistically distinct effect for seller type.[11]

Table 3. Summary Statistics for Vehicles Sold Via Auction (Used in the Price Regressions)

			Correlations											
	Mean	Standard deviation	1	2	3	4	5	6	7	8	9	10	11	12
1. *Price*	10,850	8,003	1											
2. *Mileage*	63,404	47,117	–0.60	1										
3. *VehicleAge* (years)	4.66	3.67	–0.60	0.76	1									
4. *MileageAge*	–0.08	1.24	–0.64	0.94	0.94	1								
5. *Valuation*	11,040	8,013	0.98	–0.61	–0.60	–0.65	1							
6. *VehicleSupply*	6,724	9,615	0.07	–0.32	–0.39	–0.37	0.07	1						
7. *Grade(0)*	0.01	0.08	–0.08	0.03	0.04	0.04	–0.04	–0.01	1					
8. *Grade(1)*	0.01	0.11	–0.07	0.03	0.02	0.03	–0.04	–0.01	–0.01	1				
9. *Grade(2)*	0.09	0.28	–0.10	0.05	0.02	0.04	–0.07	–0.01	–0.03	–0.03	1			
10. *Grade(3)*	0.31	0.46	0.19	–0.28	–0.31	–0.32	0.18	0.19	–0.06	–0.07	–0.21	1		
11. *Grade(4)*	0.10	0.30	0.24	–0.28	–0.27	–0.29	0.23	0.13	–0.03	–0.04	–0.10	–0.23	1	
12. *Grade(5)*	0.01	0.09	0.10	–0.09	–0.07	–0.08	0.09	0.01	–0.01	–0.01	–0.03	–0.06	–0.03	1

Notes: MileageAge is the score of the first component of a principal components analysis of *Mileage* and *VehicleAge*, which explains its high correlation with *Mileage* and *VehicleAge*. All correlations are significant at $p < 0.001$.

Table 4. Price Regressions for Transactions in the Electronic and Physical Markets

		Electronic market		Physical market	
		1	2	3	4
β_0	Intercept	–98.26	–208.85	317.15***	90.64
		(157.05)	(165.88)	(20.19)	(88.17)
β_5	*DealerSeller*		602.06		218.93*
			(344.86)		(90.02)
β_1	*MileageAge*	–425.76***	–434.11***	–39.78**	36.92
		(110.57)	(123.04)	(12.10)	(31.08)
β_6	*DealerSeller* * *MileageAge*		–168.14		–123.13***
			(211.25)		(31.85)
β_2	*Valuation*	0.99***	0.99**	0.98***	0.97***
		(0.00)	(0.00)	(0.00)	(0.00)
β_7	*DealerSeller* * *Valuation*		–0.01		0.01**
			(0.02)		(0.00)
β_3	*VehicleSupply*	–0.01	–0.01	0.00	0.00
		(0.01)	(0.01)	(0.00)	(0.00)
β_8	*DealerSeller* * *VehicleSupply*		–0.02		0.00
			(0.01)		(0.00)
$\beta_{4,0}$	*Grade(0)*	–1,125.2	–1,501.8	–3,771.66***	–3,775.89***
		(1,256.5)	(1,404.7)	(214.43)	(235.85)
$\beta_{9,0}$	*DealerSeller* * *Grade(0)*		—[a]		1,866.61***
					(247.81)
$\beta_{4,1}$	*Grade(1)*	–717.23***	–631.98**	–2,554.25***	–2,380.60***
		(201.83)	(179.85)	(157.74)	(198.39)
$\beta_{9,1}$	*DealerSeller* * *Grade(1)*		—[a]		811.91***
					(214.25)
$\beta_{4,2}$	*Grade(2)*	–746.76**	–714.07**	–1,155.71***	–913.39***
		(238.16)	(228.74)	(39.17)	(95.75)
$\beta_{9,2}$	*DealerSeller* * *Grade(2)*		106.97		122.97
			(663.34)		(114.47)
$\beta_{4,3}$	*Grade(3)*	108.05	170.69**	–59.84**	252.62**
		(81.40)	(60.41)	(22.76)	(87.85)
$\beta_{9,3}$	*DealerSeller* * *Grade(3)*		–161.96		–64.66
			(336.26)		(100.47)
$\beta_{4,4}$	*Grade(4)*	388.19***	445.86***	265.39***	631.05***
		(79.99)	(75.14)	(29.90)	(93.96)
$\beta_{9,4}$	*DealerSeller* * *Grade(4)*		157.11		–131.52
			(498.29)		(103.92)
$\beta_{4,5}$	*Grade(5)*	764.76***	831.68***	534.45***	921.28***
		(171.39)	(177.20)	(121.03)	(163.83)
$\beta_{9,5}$	*DealerSeller* * *Grade(5)*		—[a]		–227.19
					(199.82)
R^2		0.97	0.97	0.97	0.97
N		9,588	9,588	4,154,201	4,154,201

Notes: The dependent variable is *Price*. Data used in each regression are transactions in which the price was determined by auction. Estimates in columns 1 and 2 (3 and 4) are based on transactions in the electronic (physical) market. The intercept (and *DealerSeller* coefficient) represents the baseline price of a vehicle with no condition report, given the inclusion of the condition grade dummy vehicles. Robust standard errors clustered by seller are shown in parentheses. [a] There were not enough observations to estimate these coefficients. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 5. Marginal Effects of the *MileageAge* Coefficient in the Price Regressions, Reformatted by Seller Type/Market Combination

	Electronic market		Physical market	
	Dealer sellers	Commercial sellers	Dealer sellers	Commercial sellers
MileageAge coefficient	–602.25***	–434.11***	–86.21***	36.92 n.s.
MileageAge coefficient 95 percent confidence interval	[–927.70, –276.80]	[–675.67, –192.55]	[–99.90, –72.52]	[–23.94, 97.78]
MileageAge mean	–0.35	–0.87	0.55	–0.66
MileageAge standard deviation	0.89	0.46	1.25	0.91
Average change in *Price* of a unit increase in *MileageAge*	–602.25***	–434.11***	–86.21***	36.92 n.s.
Average change in *Price* of a standard deviation increase in *MileageAge*	–536.00***	–199.69***	–107.76***	33.60 n.s.
MileageAge coefficient 95 percent confidence interval * *MileageAge* standard deviation	[–825.65, –246.35]	[–310.81, –88.57]	[–124.88, –90.65]	[–21.79, 89.98]

Notes: MileageAge coefficients derived from Table 4. The *MileageAge* coefficient for commercial sellers in the electronic (physical) market is β_1 from column 2 (4) of Table 4. The *MileageAge* coefficient for dealer sellers in the electronic (physical) market is $\beta_1 + \beta_6$ from column 2 (4) of Table 4. The *MileageAge* coefficient 95 percent confidence intervals are obtained from the regression described in note 12. *** $p < 0.001$; n.s. = not significant.

The *MileageAge* coefficient for dealer sellers in the *physical* market is negative and significant ($\beta_1 + \beta_6 = -86.21$, $p < 0.001$), while the *MileageAge* coefficient for commercial sellers in the physical market is nonsignificant ($\beta_1 = 36.92$, $p = 0.24$). The evidence of adverse selection costs for dealer sellers but not commercial sellers in the physical market provides support for H1c. It also provides some evidence of the validity of the indirect test of adverse selection costs (in addition to the precedent for this test from prior literature [10, 11, 30]). This is because *MileageAge* has explanatory power beyond that of *Valuation* for vehicles for which theory suggests adverse selection risk is present (dealer vehicles in both markets and commercial vehicles in the electronic market), but not for those for which adverse selection risk is minimal (commercial vehicles in the physical market).[12]

Table 5 shows the average change in *Price* associated with a standard deviation change in *MileageAge* for each seller type/market combination. This marginal effects analysis shows that the ordering of adverse selection costs (from most to least severe) for the four combinations is dealer/electronic (−\$536, $p < 0.01$), commercial/electronic (−\$200, $p < 0.01$), dealer/physical (−\$108, $p < 0.01$), and commercial/physical (\$34, $p = 0.24$), although the scaled 95 percent confidence intervals for the marginal effects overlap for (1) dealer/electronic and commercial/electronic, and (2) commercial/electronic and dealer/physical (see Table 5).[13] The average marginal effect for vehicles sold by dealer sellers is about five times greater in the electronic market than in the physical market, which indicates that the adverse selection costs of market type exceed those of seller type for dealer sellers.

Testing H2 and H3: Sorting Between the Physical and Electronic Markets—Stock and Flow

We tested our hypotheses about the stock of vehicles in each market (H2) as follows. Based on *t*-tests, vehicles offered and sold in the electronic market are significantly newer and have less mileage than those in the physical market ($p < 0.001$; see Table 1). Table 1 shows that commercial (dealer) vehicles offered electronically are approximately 1 year (2.5 years) newer and have 15,000 (37,000) fewer miles than those offered physically. This supports H2a. Table 1 also shows that 3.6 percent of dealer seller offerings were in the electronic market (170,161/4,703,760), compared with 9.9 percent for commercial seller offerings (343,768/3,474,924). A two-sample test of proportions shows that these percentages are significantly different at $p < 0.001$. This supports H2b by showing that dealer sellers offer a lower percentage of vehicles in the electronic market than do commercial sellers.

We tested our hypotheses about the flow of vehicles between markets (H3) as follows. A total of 236,300 vehicles were offered in both markets. If sellers were equally likely to offer these vehicles first in either market, then we would expect 50 percent of them to be offered first electronically. We find that 69.1 percent ($n = 163,300$) of these vehicles were offered first electronically; a one-sample test of proportions shows that this is statistically greater than 50 percent ($p < 0.001$). This supports H3a by showing that when a vehicle is offered in both markets, it is more likely to be offered in the electronic market first. Of the 236,300 vehicles offered in both markets, 201,290 (85.1 percent) sold in the physical market, 9,318 (3.9 percent) sold in the electronic market, and the other 25,692 (10.9 percent) did not sell in either market during the study period. A one-sample test of proportions confirms that 85.1 percent is significantly greater than 50 percent ($p < 0.001$). This supports H3b by showing that when a vehicle is offered in both markets, it is more likely to sell in the physical market.

Table 6 shows the most common vehicle flow patterns, stratified by seller type. Table 7 provides additional information on vehicle flow between markets. Table 6 shows that if a vehicle is offered in both markets, it is usually offered in the electronic market first, consistent with H3a. Table 7 shows that most vehicles that are unsold when initially offered in the electronic market eventually sell in the physical market, while the converse is rarely true, consistent with H3b. These findings show that vehicle flow is mostly unidirectional from the electronic market to the physical market. Other

Table 6. Most Common Vehicle Flow Patterns, Stratified by Seller Type

Commercial sellers		
Rank	Vehicle flow	*N* (percent of total)
1	p	1,854,864 (73.8)
2	p p	199,185 (7.9)
3	e p	106,859 (4.3)
4	p -	64,288 (2.6)
5	p p p	55,813 (2.2)
6	e	34,588 (1.4)
7	e -	29,519 (1.2)
8	p p -	21,803 (0.9)
9	p p p p	21,007 (0.8)
10	p e p	16,973 (0.7)
11	e e p	10,214 (0.4)
12	p p p p p	9,570 (0.4)
13	p p p -	8,558 (0.3)
14	e p p	7,440 (0.3)
15	e e -	5,451 (0.2)
16	p p p p p p	4,661 (0.2)
17	e e	4,423 (0.2)
18	p e p p	4,137 (0.2)
19	e e e p	3,965 (0.2)
20	p p p p -	3,416 (0.1)
	Other	45,358 (1.8)
Total		2,512,092 (100.0)

Dealer sellers

Rank	Vehicle flow	*N* (percent of total)
1	p	1,588,344 (55.1)
2	p -	364,233 (12.6)
3	p p	335,260 (11.6)
4	p p -	127,590 (4.4)
5	p p p	125,055 (4.3)
6	p p p p	55,223 (1.9)
7	p p p -	54,781 (1.9)
8	e -	40,909 (1.4)
9	p p p p p	27,602 (1.0)
10	p p p p -	27,027 (0.9)
11	p p p p p p	14,914 (0.5)
12	p p p p p -	14,373 (0.5)
13	e e -	13,765 (0.5)
14	e	8,903 (0.3)
15	p p p p p p p	8,538 (0.3)
16	p p p p p p -	8,081 (0.3)
17	e p	7,737 (0.3)
18	p p p p p p p p	4,977 (0.2)
19	p p p p p p p -	4,802 (0.2)
20	e e e -	4,587 (0.2)
	Other	45,032 (1.5)
Total		2,881,733 (100.0)

Notes: Each rectangle represents a vehicle offering. The upper triangle denotes whether the offering was in the physical (white "p") or electronic (gray "e") markets. The lower triangle denotes whether the vehicle sold (black) or not (white.) A dash indicates that the vehicle disappears from the sample before we observe it to sell. For example, e p means that a vehicle was offered electronically and did not sell; it was then offered physically and sold; p - means that the vehicle was offered physically and did not sell; we do not observe it again.

Table 7. Vehicles Initially Offered in Each Market and Where They Eventually Sold

	Number of vehicles initially offered in each market	Number sold at initial offering	Number of remaining vehicles	Number of remaining vehicles that eventually . . .		
				Sold in electronic market	Sold in physical market	Disappeared
All sellers						
Electronic	313,989	43,491 (14%)	270,498	8,848 (3%)	151,867 (56%)	109,783 (41%)
Physical	5,079,836	3,443,208 (68%)	1,636,628	7,362 (0%)	912,487 (56%)	716,779 (44%)
Dealer sellers						
Electronic	92,287	8,903 (10%)	83,384	1,797 (2%)	13,719 (16%)	67,868 (81%)
Physical	2,789,446	1,588,344 (57%)	1,201,102	2,772 (0%)	587,003 (49%)	611,327 (51%)
Commercial sellers						
Electronic	221,702	34,588 (16%)	187,114	7,051 (4%)	138,148 (74%)	41,915 (22%)
Physical	2,290,390	1,854,864 (81%)	435,526	4,590 (1%)	325,484 (75%)	105,452 (24%)

Notes: Percentages listed in the three right-most columns are calculated based on the number of remaining vehicles, not the number of *total* vehicles. Percentages may not sum to 100 percent across each row due to rounding.

insights emerge from Tables 6 and 7. First, the majority of vehicles are offered initially in the physical market and are sold immediately. This suggests that the physical market is highly liquid, to which we return below. Second, the vehicle flow patterns vary between dealer and commercial sellers, with commercial sellers more likely to use the electronic channel, consistent with H2b. Third, dealer vehicles are more likely to disappear from the sample than commercial vehicles. As discussed above, this is likely because dealer sellers have the option to sell a vehicle retail if they cannot sell it wholesale, whereas commercial sellers do not (in general). Fourth, vehicles are more likely to sell when offered physically than electronically. This holds regardless of seller type or whether an offering is an initial or subsequent offering.

Testing H4: Buy Now Prices in the Electronic Market

H4 posits that sellers set Buy Now prices above market value in the electronic market. Table 8 shows that 96.8 percent of all electronic offerings have a Buy Now price and that 83.9 percent of electronic market transactions are Buy Now transactions. Sellers set Buy Now prices at 108 percent (on average) of their *Valuations.* Vehicles that *sell* for the Buy Now price sell for 102 percent of their *Valuations. t*-tests show that Buy Now prices significantly exceed vehicles' *Valuations* ($p < 0.001$). This is true for all offerings as well as for sold vehicles, both for the pooled data and stratified by seller type. This supports H4. This also illustrates that although buyers are price sensitive in the electronic market (i.e., they tend to use the Buy Now option on the *least* overpriced vehicles), they still pay more than market value. We explore possible reasons for this below. On the surface, the evidence of above-market pricing in the electronic market may seem incompatible with the evidence of discounts due to adverse selection in the electronic market. We resolve this as follows. Recall that the adverse selection costs analysis is based on transactions in which the price was determined by auction (given the theoretical requirements for adverse selection), while the above analysis is based on transactions in which the price was posted. Thus, the two analyses are not directly comparable. However, to investigate this further, we used logistic regression to model the probability that a vehicle purchased in the electronic market was purchased via the Buy Now option (versus via auction). We regressed *BuyNowPurchase* on *Valuation*, *MileageAge*, *VehicleSupply*, and the *Grade* dummies (see Table 2). The coefficient for *MileageAge* is –0.20 (standard error = 0.02), indicating that older vehicles with higher mileage—if they are purchased in the electronic market—are more likely to be purchased via auction than via the Buy Now option. As additional evidence of this, the median values of *VehicleAge* for vehicles purchased via the Buy Now and auction mechanisms in the electronic market are 1.52 years and 2.76 years, respectively, which are statistically different at $p < 0.001$ (based on a Mann–Whitney test). Thus, the above-market prices apply primarily to the newer vehicles for which adverse selection risk is minimal and that are purchased via the Buy Now option, while the adverse selection discounts apply primarily to older vehicles that are purchased via auction.

Table 8. Buy Now Prices and Related Statistics for Vehicles in the Electronic Market

	Vehicles offered	Vehicles offered with a Buy Now price				Vehicles sold	Vehicles sold via the Buy Now option			
	N	*N*	Buy Now price: mean (SD)	Valuation: mean (SD)	Buy Now price/ valuation	*N*	*N*	Price: mean (SD)	Valuation: mean (SD)	Price/ valuation
All sellers	513,929	497,607	17,391 (10,242)	16,023 (9,525)	1.08	59,701	50,113	17,368 (11,239)	16,984 (10,879)	1.02
Dealer sellers	170,161	162,149	17,579 (15,305)	15,305 (12,545)	1.15	13,462	12,976	18,099 (17,335)	17,451 (16,748)	1.04
Commercial sellers	343,768	335,458	17,294 (7,759)	16,392 (7,486)	1.06	46,239	37,137	17,116 (8,117)	16,823 (7,888)	1.02

Notes: t-tests indicate that Buy Now prices significantly exceed Valuations for all rows, both for vehicles offered and vehicles sold ($p < 0.001$).

Alternative Explanations and Robustness Checks

Robustness Check—Retail Margins and Transport Costs

We considered whether buyers' retail margins and vehicle transport costs might be alternative explanations for some of our results. First, buyers may make a higher margin when they retail relatively new vehicles than when they retail older vehicles. As such, they may be willing to pay full wholesale market value for newer vehicles but not for older vehicles, which could represent an alternative explanation for the discounts we observe in our tests of H1. We find this explanation unlikely. If differential retail margins were responsible for the discounts that we observe, then we should see buyers discounting *all* older vehicles instead of only those that contain adverse selection risk.

Second, it is possible that buyers may purchase more remotely when using the electronic market than when using the physical market, which would lead to higher vehicle transport costs in the electronic market. This may cause buyers to discount what they pay in the electronic market, particularly for older (and hence lower-margin) vehicles, which could represent an alternative explanation for the discounts we observe in our tests of H1. To examine this, we reestimated the price regressions (excluding the *DealerSeller* interaction terms, see Equation (1)) by limiting the observations to only those for which the distance between vehicle and buyer was 100 miles or less.[14] If the lower margin/transport cost alternative explanation is responsible for the discounts we observe, then the *MileageAge* coefficient in these regressions should be similar for both electronic and physical market transactions, because potential differences in transport costs between the two markets will be negligible. The *MileageAge* coefficients for these regressions are –392 (standard error = 138.4; $p < 0.01$) and –25 (standard error = 12.6; $p < 0.05$) for the electronic and physical market transactions, respectively, the 95 percent confidence intervals for which do not overlap. These coefficients are similar to those reported in Table 4 and fall within the 95 percent confidence intervals for the *MileageAge* coefficients reported there (see columns 1 and 3). For this "within 100 miles" subsample, the marginal effect of a one standard deviation increase in *MileageAge* is –\$182 for electronic transactions and –\$32 for physical transactions; the corresponding marginal effects for the full sample (see Table 4, columns 1 and 3) are –\$214 and –\$50. We obtain similar results when estimating the regressions for other distance ranges. This shows that the differential discounts between the electronic and physical markets hold even when differences in transport costs between markets are likely to be minimal. Thus, it is unlikely that our results are driven by differences between the two markets in margin or transport costs.

Robustness Check—Buyer Segmentation and Location

To assess whether our results for H1 could be biased by unobserved differences in the buyers who purchased vehicles in each market, we repeated several analyses using only those vehicles purchased by buyers who used both markets, that is, "multimarket" buyers. Table 9 shows that multimarket buyers represent 7.0 percent of the buyers, although they represent a disproportionate percentage (19.0 percent) of the transactions. The results of retesting H1 for the "multimarket" buyer subsample are consistent with

Table 9. Summary Statistics for Buyers Who Purchased in Each Channel

		Number of vehicles purchased		
			In the electronic market	
	N	In the physical market	Via Buy Now option	Via auction
Buyers who used only the electronic market	420	0	2,806	837
Buyers who used only the physical market	86,510	3,408,472	0	0
Buyers who used both markets	6,592	745,729	47,307	8,751

Notes: Buyer counts based on the *BuyerID* variable in the data (see Table 2).

the results of the main analysis (excluded here for brevity of presentation). We also repeated the logistic regression for whether a vehicle that is sold in the electronic market is sold via the Buy Now option using only those vehicles purchased by multimarket buyers, and we recalculated the Buy Now premiums paid by multimarket buyers (see below). The results are similar to the main results.

We also considered whether the results might be driven by buyers' geographic location. For example, buyers that purchase from the electronic market could be those that are located in rural areas and that lack access to physical market facilities. This is unlikely because the majority of the buyers (94.0 percent) who purchased in the electronic market are multimarket buyers who clearly have access to physical market facilities. We also used the *BuyerZip* field to plot the location of the buyers who made purchases in the electronic market. The location of these buyers is similar to that of the entire buyer population.

Alternative Explanations for Premium Buy Now Prices in the Electronic Market

As discussed in the motivation for H4, we believe that when buyers use the Buy Now option to pay a premium for relatively new vehicles in the electronic market, they do so because of the immediacy of the transaction. For example, a buyer (who is a dealer) may need a specific vehicle that he does not have in inventory, such as one requested by a retail customer [28]. If the buyer has negotiated a retail price for the vehicle with the retail customer, and he can purchase it from the electronic market, then he may be willing to pay a relatively high wholesale price because he already knows his profit margin. The Buy Now option allows him to purchase the vehicle without risking losing it in an auction, and this security and immediacy may justify the premium price. For their part, sellers attempt to appropriate the value that buyers place on the immediacy of the electronic market by setting high Buy Now prices. This approach generates little risk for the seller, because if buyers pay the premium, then the seller benefits, and if buyers do not pay the premium, then the seller can shift the vehicles to the physical market, where she is likely to receive market value. The option to shift vehicles between markets/channels may also explain why dealer sellers set higher Buy Now prices in the electronic market than do commercial sellers (see Table 8), because the former can sell vehicles through their retail operations as well as in the wholesale market.

We considered alternative explanations. One possibility is that buyers pay a premium for vehicles in the electronic market because they are not available in the physical market. This is unlikely for two reasons. First, Tables 6 and 7 illustrate that most vehicles offered in the electronic market are later made available in the physical market. Second, we find no evidence that vehicles offered in the electronic market are rarer than vehicles offered in the physical market. We examined this via the *VehicleSupply* variable. Lower values of *VehicleSupply* indicate greater rarity. We regressed *Electronic* on a constant, *MileageAge*, *Valuation*, *VehicleSupply*, and the *Grade* dummies (using logistic regression; see Table 2).[15] If sellers are more likely to offer rare vehicles electronically, then the *VehicleSupply* coefficient should be negative and significant. However, the *VehicleSupply* coefficient is not significant ($\beta = -0.00$, $p = 0.36$). We also examined whether *VehicleSupply* might explain which vehicles *sell* in each market. The median value of *VehicleSupply* is smaller for vehicles sold electronically than physically (2,605 versus 3,072; $p < 0.001$ via a Mann–Whitney test), but the mean value is larger (7,447 versus 6,113; $p < 0.001$ via a t-test.) Overall, there is little evidence that "rare" vehicles are transacted electronically while "common" vehicles are transacted physically.

Another alternative explanation relates to differences in buyers' transaction costs (excluding adverse selection costs) when using the physical and electronic markets. Prior research has argued that buyers in the electronic market save the transaction costs associated with a trip to a physical market facility and that they apply these savings to a higher purchase price [16, 28]. This might explain the premium prices for the subset of vehicles purchased via the Buy Now option. We find this explanation unlikely. There are 7,012 buyers who purchased via the electronic market in the sample (see Table 9). On average, these buyers paid \$318 more than vehicles' *Valuation* for Buy Now purchases in the electronic market (median = \$250). If a buyer purchases one vehicle when he visits a physical market facility, then the transaction costs of the visit must exceed \$318 (on average) to account for the premium he would pay for that vehicle in the electronic market via the Buy Now option. However, most buyers purchase more than one vehicle per physical market facility visit. Buyers who purchased in the electronic market purchased an average of 3.46 vehicles per physical market facility visit (median = 2). If these buyers purchased the same 3.46 vehicles electronically via the Buy Now option, the total price of the vehicles would be approximately \$1,100 higher. For many buyers, this would likely exceed the transaction costs of a trip to a physical market facility.

The Role of the Two Markets

We considered the overall pattern of evidence to address our research question about the role of the physical and electronic markets and why they coexist. We conclude that the electronic market serves as a spot market for fulfilling unanticipated demand for relatively new vehicles and the physical market serves as the general exchange for all types of vehicles, both new and old. This conclusion is consistent with (1) buyers paying premium prices for relatively new vehicles in the electronic market via the Buy Now option, (2) the substantially higher liquidity of the physical market, and (3) the fact that most vehicles listed in the electronic market are unsold and later moved to the physical market. We presented several other theoretical possibilities for the role of the two markets in the literature review, and we ruled them out as follows.

One possibility is that one market serves as an overflow channel for unsold vehicles from the other market. The vehicle flow analysis illustrates that unsold vehicles almost never flow from the physical market to the electronic market, which rules out the possibility that the electronic market serves as an overflow channel for vehicles unsold in the physical market. The flow analysis also shows that the most common vehicle flow pattern was for the vehicle to be offered in the physical market and sold at its first offering. This means that characterizing the physical market as simply an overflow channel for unsold vehicles from the electronic market would misrepresent the role of the physical market. A second possibility is that the role of the markets is defined by vehicle supply, such that common vehicles (e.g., Ford Taurus) are traded in one market, while rare vehicles (e.g., Jaguar X-Type) are traded in the other market. As discussed above, this is unlikely, given that there is little evidence of a "long tail" in either market. A third possibility is that the role of the two markets is defined by vehicles' observable quality. There is some evidence to suggest this. Table 1 shows that the average mileage and age of vehicles is lower in the electronic market than in the physical market. Our results suggest that this is because the adverse selection costs for older vehicles in the electronic market cause sellers to favor the electronic market for newer vehicles for which adverse selection costs are minimal. However, any characterization that newer vehicles trade electronically while older vehicles trade physically is incomplete and misleading, because a strong supply of newer vehicles are traded physically as well. Figure 1 shows histograms of the mileage and age of vehicles offered in each market and illustrates that the difference in average mileage and age is driven by the lack of older vehicles in the electronic market, not by the lack of newer vehicles in the physical market. One reason why newer vehicles continue to be traded physically is that many are moved to the physical market after not selling in the electronic market (see Tables 6 and 7). Essentially, the lower likelihood of sale in the electronic market ensures a large supply of newer vehicles for the more liquid physical market (see Tables 1, 6, and 7).

Discussion

Summary of Results and Differences from Prior Research

We analyzed over 8 million transactions in the U.S. wholesale used vehicle market, comparing transactions in the physical market to those in an electronic market. We conclude that the physical market is much more liquid than the electronic market. In fact, most vehicles that are initially offered in the electronic market sell in the physical

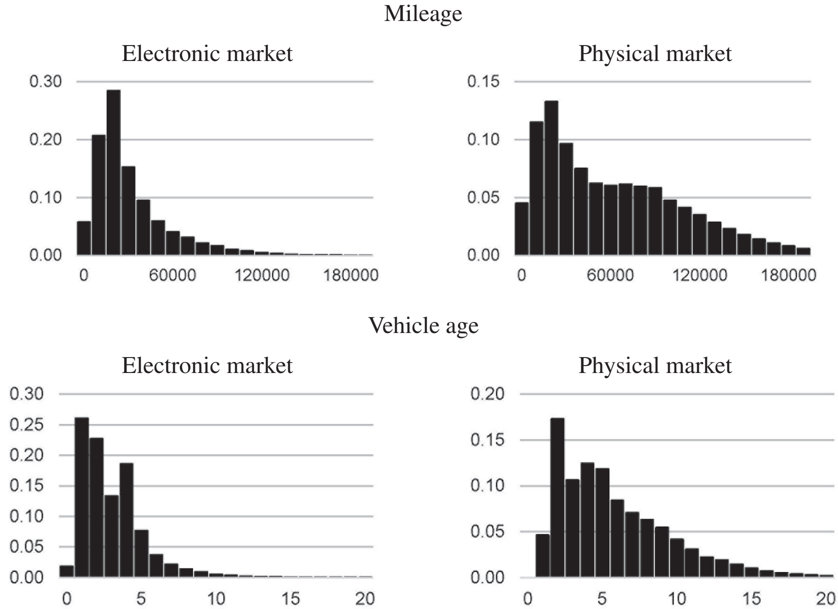

Figure 1. Histograms of Vehicle Mileage (Truncated at Mileage = 200,000) and Age by Market

market. We find evidence of adverse selection costs for older vehicles in both markets, although these costs are much greater in the electronic market and are limited to vehicles sold by dealer sellers in the physical market. This causes sellers to offer mostly newer vehicles—for which adverse selection risk is low—in the electronic market, and the majority of the electronic transactions for these newer vehicles are conducted via a fixed Buy Now price set by the seller. Buyers pay a premium when purchasing via the Buy Now option, which we attribute to the value that buyers place on the immediacy of the Buy Now option in the electronic market. The average age and mileage of vehicles is lower in the electronic market, but that is due to the lack of older vehicles in the electronic market, not to the lack of newer vehicles in the physical market. The overall pattern of our results allows us to conclude that the electronic market serves as a spot market for fulfilling unanticipated demand for relatively new vehicles, while the physical market serves as the general exchange for all types of vehicles.

Our data consist of transaction-level data from both the physical and electronic markets, and we are able to track vehicle flow between markets using the Vehicle Identification Number. Given this granularity, our analysis is more detailed than that conducted in prior research in this stream. Perhaps not surprisingly, our results differ from prior research. First, Wolf and Muhanna [30, see p. 854] concluded that older vehicles with higher mileage were more likely to sell on eBay, with the implication that newer vehicles with lower mileage were sold in the physical market. We find the opposite. This discrepancy may stem from data availability, as our transaction data from both markets (Wolf and Muhanna studied electronic transactions only) allow us to investigate product sorting between markets directly. Second, Garicano and Kaplan [10] found no evidence of adverse selection costs in the electronic market in their analysis, whereas we do. This is likely because there were restrictions on the type of vehicles that could be offered in the electronic market they studied. Because there were no such restrictions in our context, we could conduct a purer test of adverse selection costs and show their existence for older vehicles. Third, Overby and Jap [25] compared physical and electronic buying channels and concluded that vehicles of predictable quality, which include vehicles of both very high and very low observable quality, traded effectively electronically. By contrast, we observe few vehicles of very low observable quality in the electronic market (see Figure 1). This is because we study a standalone electronic market that functions as a "spot" market, whereas Overby and Jap studied an electronic access channel that augments the physical market. Buyers are unlikely to need very low observable quality vehicles on a "spot" basis, which explains the lack of such vehicles in the electronic market in our context.

Limitations

Although our study is focused on the wholesale used vehicle industry, the conclusions are relevant to other industries. For example, the trade-off that we study between low participation costs and high adverse selection costs in electronic markets is a general phenomenon found in many industries (e.g., [7, 14]). Thus, our findings may inform how products are sorted between physical and electronic markets in other industries and wholesale trading environments. Also, as electronic markets emerge in other industries, sellers and buyers may experiment with these markets while relying on the physical market as a "fallback" option, as they do in our context. One characteristic of this industry that may limit the generalizability of the findings is that vehicles are rarely offered simultaneously in the two markets. In other industries, simultaneous offerings may be the norm. However, our results should be applicable to contexts in which sellers divide their inventory between markets, which they will do if they have episodic access to a physical market or if they must protect against selling the same product twice. Industries in which this may be the case include those for vehicles, heavy machinery, livestock, crops, flowers, and rare art.

Another limitation of our study is that our measurement of vehicle supply is not as granular as we would like. For example, we do not have data on vehicle color or option packages. It may be that buyers use the electronic market to purchase vehicles that appear to be reasonably common (as we conclude), but that are actually rare because they are of unusual color or have a rare option package. We cannot rule this out. Also, our results may be idiosyncratic to the time period that we observe, a common limitation in most empirical research. However, we believe the results are likely to hold for other time periods, because electronic trading continues to be relatively rare in this and many other industries in which it has been introduced.[16] Another limitation is that we do not observe sellers' cost structures or technological savvy. For example, dealer sellers may be less likely than commercial sellers to list vehicles in the electronic market (see H2b) because they lack technological savvy. We find this unlikely, given that creating an electronic listing is not difficult and that most dealers have experience with listing vehicles electronically via AutoTrader.com, eBay, etc., but we cannot rule it out. Also, it is possible that potential differences in transport costs between the two markets are responsible for the discounts we observe in our tests of H1, although—in light of our robustness checks—this fraction is likely to be small (and perhaps zero). Also, the number of auction transactions for dealer sellers in the electronic market may be too low for us to identify a statistically distinct effect of seller type on adverse selection costs in the electronic market (see our tests of H1). It is possible that this effect would become apparent with additional data. Last, although our theory and explanations are consistent with the full pattern of our results and we have ruled out several alternative explanations, there may be other explanations that fit the data.

Conclusion

Markets can improve the efficiency of exchange between buyers and sellers, but effective design is critical to achieving the benefits that markets can provide. Comparative studies of physical and electronic markets increase our understanding of how market design influences market outcomes, and we contribute to this literature in several ways. First, we study multiple sources of adverse selection risk for buyers, including not only risk created by electronic product presentation but also risk created by uncertainty about product quality and seller reputation. This permits a nuanced examination of how different sources of uncertainty interact to create adverse selection risk in electronic markets, which can inform decisions about how to sort products between physical and electronic markets. Second, we study the flow of products between the physical and electronic markets over time, thereby documenting dynamics in how buyers and sellers use the markets that have not previously been shown. Third, we study how sellers and buyers use an electronic market when the physical market provides a viable "fallback" option. This improves understanding of how traders use physical and electronic markets synergistically in the trading process.

Another contribution of our analysis is that we draw empirically grounded conclusions on the role of the two markets for wholesale trading. Because physical and electronic markets are likely to coexist for the foreseeable future, understanding their roles can help market participants and market designers optimize the experience in each market. For example, we find that the electronic market serves as a spot market for unanticipated inventory needs from retail customers. As such, a useful design feature would be a "retail view" that allows retail customers to see details of the wholesale listing without divulging wholesale price information. Also, our study illustrates that electronic markets can provide convenience and immediacy by permitting purchases at any time—but only if the proper price mechanism (Buy Now instead of auction) is available.

Our analysis also yields new insights into how sellers and buyers manage the trade-offs between adverse selection costs and other transaction costs in physical and electronic markets. This helps us understand how information technology can be used to improve market function. For example, electronic markets may be more efficient than physical markets given their ability to aggregate a large pool of potential trading partners, but these benefits may be outweighed by adverse selection costs. Thus, we might expect for electronic markets to be most effective for products of low quality uncertainty, with physical markets better suited for high uncertainty products. Although such an outcome might improve efficiency, it might not be achieved without other design and policy considerations. For example, sellers may recognize the value that buyers place on the convenience and immediacy of the electronic market and demand premium prices that stunt the development of the electronic market. In such a case, it may be useful for the operator of the electronic market to monitor pricing and other behavior to stimulate enough use of the market to generate the associated benefits.

Notes

1. Another example of a direct test is found in Edelman [9], although his analysis relates to Web site quality rather than to product quality. His analysis represents a direct test because he assessed quality using sophisticated Web site probing software; this provided him with quality information that was not available to general users of the Web sites.

2. It is rare for a vehicle to be offered in both markets simultaneously. Most sellers close the electronic listing before offering a vehicle physically to prevent the vehicle from being purchased by two different buyers. Of the instances in which a vehicle was offered electronically and then physically, the electronic listing was still open when the vehicle was offered physically only 12 percent of the time. For these cases, we recorded the flow as electronic to physical.

3. Many of the vehicles that disappeared from the sample may have been reoffered in the market after the close of our data collection. Also, many vehicles that appear to us as sold upon their initial offering may have been offered prior to the beginning of our data collection. To investigate the bias that this might create, we analyzed the flow of only those vehicles that were offered initially no sooner than January 2007 (i.e., one month after the beginning of our data) and no later than September 2007 (i.e., one month before the end of our data). These results are similar to those reported.

4. To illustrate the limitations of vehicle history reporting services for revealing hidden quality information, we quote the following disclaimer from CARFAX. "CARFAX does not have the complete history of every vehicle. A CARFAX Vehicle History Report is based only on information supplied to CARFAX. Other information about the vehicle, including problems, may not have been reported to CARFAX. Use a Vehicle History Report as one important tool, along with a vehicle inspection and test drive, to make a better decision about a used car" (www.carfax.com/about/data_sources.cfx). For a similar disclaimer, see www.vehiclehistory.gov/CAPDisclaimerSUMMARY062112.pdf.

5. Physical market facilities are typically open for transactions 1–2 days per week, known as "sale days."

6. The diffusion of the electronic market has been slow. As of 2012, transactions in the electronic market still comprised a small fraction (4.4 percent) of total transaction volume (source: 2012 NAAA Annual Review, www.naaa.com/pdfs/2013AnnualReview.pdf, p. 8). As another example, diffusion of electronic commerce for overall retail sales has also been slow, taking 13 years to rise from approximately 0 percent in 1999 to approximately 6 percent in 2012. Source: U.S. Census (www.census.gov/retail/).

7. This is consistent with Kim and Ratchford's [15] finding of increased use of the Internet to search for vehicles, although they study the retail market rather than the wholesale market.

8. Specifically, $MileageAge = 0.7071 * \text{std}(Mileage) + 0.7071 * \text{std}(VehicleAge)$, where "std" means the standardized value of the variable.

9. All *Grade*(*g*) dummy variables = 0 for vehicles without condition reports. As a result, we can include all *Grade*(*g*) dummy variables without introducing perfect collinearity with the intercept.

10. Most of the variance in *Price* is explained by *Valuation* (see their 0.98 correlation in Table 3). This is desirable because the indirect test of adverse selection costs relies on the reference price being a good proxy for the actual price. We confirmed that the *DealerSeller* interaction terms added explanatory power via an F-test of exclusion restrictions. The F-statistic was significant for the regressions when estimated using either the electronic or physical market transactions ($p < 0.01$).

11. Although $n = 486$ is small relative to the number of auction transactions for the other seller type/market combinations, it is comparable to the sample sizes for sold vehicles used in prior research. For example, $n = 333$ in Wolf and Muhanna [30], $n = 853$ in Garicano and Kaplan [10], and $n = 527$ in Genesove [11].

12. To explore additional differences across the seller type/market combinations, we fitted the following variant of Equation (1). $Price = \Sigma_{j=1}^{4} I_j * [\beta_{0,j} + \beta_{1,j} * MileageAge + \beta_{2,j} * Valuation + \beta_{3,j} * VehicleSupply + \Sigma_{g=0}^{5} \beta_{4,g,j} * Grade(g)] + \varepsilon$, where I_j is an indicator variable for each seller type/market combination j. This model yields the same results as fitting $Price = \beta_0 + \beta_1 * MileageAge + \beta_2 * Valuation + \beta_3 * VehicleSupply + \Sigma_{g=0}^{5} \beta_{4,g} * Grade(g) + \varepsilon$ for each seller type/market combination individually (it also yields the same results as fitting Equation (1)). Because the model estimates the coefficients for each combination simultaneously, it allows us to test whether the coefficients differ significantly across the four combinations using an F-test for the equality of regression coefficients. The *MileageAge* coefficients are significantly different ($p < 0.01$) across each combination except for the dealer/electronic and commercial/electronic combinations.

13. We calculated the scaled 95 percent confidence intervals for each marginal effect by multiplying the standard deviation of *MileageAge* for each seller type/market combination by the 95 percent confidence intervals for the corresponding $\beta_{1,j}$ coefficients from the regression described in note 12.

14. We measured the distance between vehicle and buyer as (1) the distance between the zip code of the facility at which the vehicle was located and the buyer' zip code (for physical market transactions and for vehicles sold by commercial sellers in the electronic market), and (2) the distance between the dealer seller's zip code and the buyer's zip code (for vehicles sold by dealer sellers in the electronic market).

15. *Valuation* is not recorded in the data for vehicles that were offered in the physical market but not sold. We imputed *Valuation* for these observations as follows. First, we grouped vehicles by year, make, and model (e.g., 2007 Honda Accord). We then took the sold transactions for each group *in a given calendar year* and regressed *Price* on *Mileage*. We used the resulting coefficients, including the intercept, to calculate the predicted *Price* for each vehicle of that year, make, and model that was offered *in the same calendar year* but did not sell. We used this as the imputed value of *Valuation*. We were unable to impute *Valuation* for vehicles for which there were fewer than two observations in the regression. We dropped these observations ($n = 8{,}491$). Because our method for estimating *Valuation* is unlikely to be as accurate as that used by the firm that provided the data, we ran the regression with and without this variable. Without this variable, the *VehicleSupply* coefficient remains nonsignificant ($\beta = -0.00$, $p = 0.19$).

16. See note 6.

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