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Electronic and Physical Market Channels: A Multiyear Investigation in a Market for Products of Uncertain Quality

Eric Overby
College of Management, Georgia Institute of Technology, Atlanta, Georgia 30308,
eric.overby@mgt.gatech.edu

Sandy Jap
Goizueta Business School, Emory University, Atlanta, Georgia 30322,
sandy_jap@bus.emory.edu

Many markets that have traditionally relied on collocation of buyers, sellers, and products have introduced electronic channels. Although these electronic channels may provide benefits to buyers and sellers by lowering the transaction costs of participating in the market, there are trade-offs related to quality uncertainty and increased risk that may limit the adoption of the electronic channels. As a result, buyers and sellers use physical channels for some transactions and electronic channels for others. These usage patterns may evolve over time, particularly when the electronic channels are new. We examine buyer and seller use of electronic and physical channels in a market for products of uncertain quality (used vehicles) over a 2.5-year period. Results indicate that transactions involving low quality uncertainty and relatively rare products occurred in the electronic channels, whereas transactions involving high quality uncertainty and relatively plentiful products occurred in the physical channels. These patterns became clearer over time as buyers and sellers gained experience with the electronic channels. The electronic channels led to discounts for products of high quality uncertainty, but not for those of low quality uncertainty.

Key words: physical markets; electronic markets; market channels; business-to-business auctions; quality uncertainty; adverse selection; market design; transaction costs; change over time; wholesale automotive
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1. Introduction

Markets that have traditionally relied on collocation of buyers, sellers, and products are steadily transitioning to electronic forums. In some cases, separate electronic markets have been launched as an alternative to the incumbent physical market. In other cases, new electronic channels have been added to the physical market, causing the market to take on a hybrid structure. The motivation behind these transitions is the possible benefits that electronic channels create. However, there are trade-offs that may limit the use of electronic channels. For buyers, electronic channels may reduce search costs (Bakos 1997), particularly for rare products (Brynjolfsson et al. 2003), but they may also increase risk (Dewan and Hsu 2004). For sellers, electronic channels may reduce presentation and other transaction costs (Kambil and van Heck 1998), but they may also lead to discounts due to quality uncertainty (Koppius et al. 2004). Other factors that may influence the use of electronic channels include interdependencies between buyer and seller behavior, because how buyers use the channels affects how sellers use them and vice versa, and time, because use may evolve as buyers and sellers adapt to the channels.

In this study, we explore the introduction of electronic channels into an established physical market, considering the factors above. The empirical context is the wholesale automotive market, which is a business-to-business market for used vehicles that has traditionally operated via collocation of buyers, sellers, and vehicles. Two electronic channels have recently been introduced to the market. First, buyers may participate in the market via either the legacy physical channel or a new electronic channel. Second, sellers may present vehicles via either the legacy physical channel or a new electronic channel. The data span 2.5 years, beginning during the implementation of the electronic channels. The research questions focus on how buyers and sellers used this mixture of channels over time.

Results indicate that transactions involving rare vehicles and vehicles of predictable quality, i.e., those with low quality uncertainty, occurred in the electronic channels, whereas transactions involving more commonly available vehicles and vehicles of unpredictable quality occurred in the physical channels. For example, sellers were as much as 50% more likely to use the electronic channel for a vehicle of predictable quality than one of unpredictable quality. This is likely because there was no significant price discount associated with electronic presentation of predictable quality vehicles, whereas there was for unpredictable quality vehicles (usually about \$600). As a result, sellers tended to use the physical channel for unpredictable quality vehicles, despite the higher presentation cost of this channel. With respect to vehicle availability, for each additional 1,000 vehicles of a given year, make, and model presented in the market, sellers were 3.8% more likely to present a vehicle of that year, make, and model in the physical channel than in the electronic channel.[1] Buyers using the electronic channel were located approximately 400 miles farther away from the market facility than buyers using the physical channel, and they used this expanded reach to purchase relatively rare vehicles unlikely to be available in their local geographies. These patterns became clearer over time as buyers and sellers gained experience with the electronic channels.

By exploring how buyers and sellers use electronic and physical market channels over an extended period of time, we extend the literature on electronic markets in several ways. First, we investigate the evolution of channel use over a 2.5-year time period. Much of the prior work has analyzed narrower cross sections, which cannot reveal the dynamics of market evolution, particularly for newly introduced electronic channels. Second, we examine how multiple factors, including quality uncertainty, seller transaction costs related to product presentation, and buyer transaction costs related to travel and search—which may have opposing effects when considered in isolation—collectively influence use of the electronic channels. Much of the prior work has focused on a single factor, such as buyer search costs or quality uncertainty (e.g., Brynjolfsson and Smith 2000, Dewan and Hsu 2004). Third, we illustrate that buyer use of electronic channels influences seller use and vice versa. Examining these participant interdependencies complements studies that have focused on either buyer or seller behavior in isolation (e.g., Koppius et al. 2004, Kuruzovich et al. 2008, Thomas and Sullivan 2005). Fourth, we investigate a single market in which both electronic and physical channels coexist. This differs from the majority of studies in this stream, in which outcomes from a physical market are compared to those from a corresponding, but discrete, electronic market for the same products (e.g., Garicano and Kaplan 2001, Kazumori and McMillan 2005, Lee 1998). The advantage of the present study's design is that it controls for a range of market policy variables, including how prices are discovered, how disputes are resolved, etc., that might otherwise become confounded with whether transactions occurred in a physical or electronic environment.

The next section of the paper describes the empirical context, research design, and research questions. Section 3 presents the hypotheses. Section 4 presents the data. Section 5 presents the empirical analysis. Section 6 discusses the results. Section 7 summarizes the study and its implications.

2. Empirical Context and Research Questions

The empirical context is the wholesale automotive market. Sellers in the market include rental car companies, the financial affiliates of automotive manufacturers, and other operators of vehicle fleets. For example, a rental car firm may use the market to dispose of large volumes of vehicles no longer suitable for rental. Buyers are automobile dealers who purchase vehicles to resell to the consumer public.[2] We based the study on transactions facilitated by one of the intermediaries in the market.

Traditionally, the intermediary has operated a physical market: buyers, sellers, and vehicles are collocated at a market facility. There are physical market facilities located throughout the United States. During a *sales event*, hundreds of vehicles are driven—one at a time—into the midst of a group of buyers and left idling for approximately 30 seconds. During this time, an auctioneer solicits bids in an ascending auction. At the end of the bidding period, the vehicle's seller signals to the auctioneer whether he will accept the highest bid, or if the vehicle will remain unsold. Thus, there is no predetermined reserve price; the "reserve" is set by the seller after all bids have been received. The next vehicle is then driven into place and the process repeats. The intermediary collects a fee from the seller for each vehicle presented in the sales event, as well as a fee from each winning buyer. Another description of this type of market, circa 1989, is provided by Genesove (1993), although some of the particulars have changed over the years.

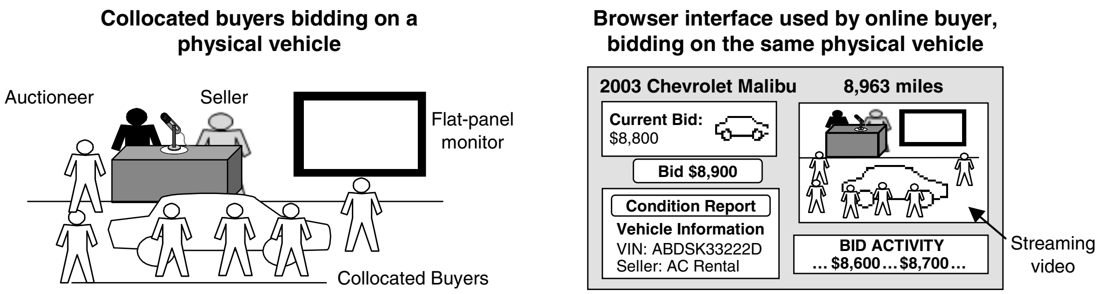
2.1. Introduction of Electronic Channels

The intermediary introduced an electronic participation channel to the market in 2002. This channel

[1] According to the 2007 National Auto Auction Association annual report (available at http://www.naaa.com), approximately 16,000,000 vehicles were offered in the market in 2007.

[2] Dealers may also sell vehicles in the wholesale market. Our data do not include any "dealer as seller" transactions.

Figure 1 **Collocated and Online Buyer Participation Channels for *Physical* Vehicles**

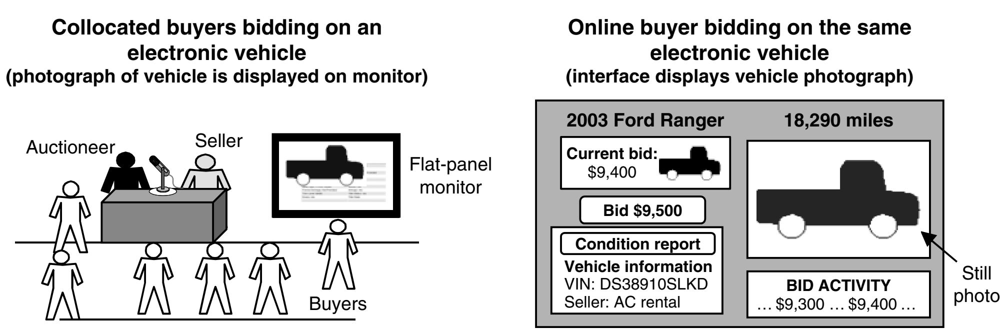


allows buyers to participate in traditional physical sales events via an Internet webcast, which provides streaming video and audio of the sales event as it is occurring at the physical market facility. Thus, buyers can use one of two *buyer participation channels*: physical attendance at the market facility or electronic participation via the Internet webcast. Both channels operate simultaneously, meaning that each sales event has a group of buyers who are physically present at the facility (referred to as *collocated buyers*) and a group of buyers who are participating via the Internet (referred to as *online buyers*). Collocated and online buyers compete with each other for the same vehicles. Collocated buyers bid on the vehicle in front of them, while online buyers bid on that same vehicle, which they experience via the video/audio stream rendered in a web browser. Figure 1 illustrates the two buyer participation channels.

After the initial implementation of the online participation channel, many collocated buyers complained that competing bids purportedly placed by online buyers were fake, i.e., shill bids, because they could not observe these bids. To combat this, the intermediary installed flat-panel monitors at the physical facility, which flash red and display the name of any online buyer who places a bid. In 2003, the intermediary decided to leverage the flat-panel monitors to introduce another electronic channel. Sellers were given the option to present vehicles by displaying a photograph and textual description of the vehicle's characteristics on the monitor. Thus, sellers can use one of two *vehicle presentation channels*: the traditional, physical channel of having the vehicle driven through the facility or the new electronic channel. Many sellers use both channels in the same sales event, alternating between them. For example, the seller might present the first two vehicles physically (referred to as *physical vehicles*), and the next two electronically (referred to as *electronic vehicles*). Figure 1 illustrates how collocated and online buyers experience *physical* vehicles. Figure 2 illustrates how collocated and online buyers experience *electronic* vehicles. As shown in Figure 2, collocated buyers view the vehicle photograph and information on the flat-panel monitor, while online buyers view the same photograph and information on the browser interface, in place of the streaming video they receive for physical vehicles. Regardless of how a vehicle is presented, the bidding process is identical: the auctioneer solicits bids from both the collocated and online buyers, after which the seller decides whether to accept the highest bid.

To summarize, collocated and online buyers bid against each other for each vehicle, whether it is presented physically or electronically. Note that sellers choose between electronic and physical presentation for each vehicle, whereas buyers choose between collocated and online participation for each sales event, in which many vehicles are presented. To complement this description, we encourage readers to

Figure 2 **Physical and Electronic Buyer Participation Channels for *Electronic* Vehicles**



watch a two-minute animation clip, available in the e-companion.[3]

2.2. Scope of the Research Questions

We use this context to pose four research questions. First, what influences sellers' decisions to present vehicles via the physical or electronic channel? Second, how does physical versus electronic vehicle presentation affect price? Third, what influences whether the winning bid is placed by a buyer using the online channel or a buyer using the collocated channel? Fourth, how do these aspects evolve over time?

We do not investigate buyers' choices of whether to use the collocated or online participation channel. We base our conclusions about buyer behavior on the types of vehicles they purchase after they have chosen a channel, i.e., how they use the channels, not on how they initially choose the channel. Readers interested in how buyers choose between channels are referred to Neslin et al. (2006).

2.3. Control Afforded by the Study's Design

The design of this study is atypical. The typical design of studies in this stream is to compare a physical market to a corresponding, but discrete, electronic market for the same products (e.g., Banker and Mitra 2005, Clemons and Weber 1996, Garicano and Kaplan 2001, Kazumori and McMillan 2005, Lee 1998). A key challenge with the physical market versus electronic market design is that the two markets usually differ beyond the physical/electronic distinction. These additional differences represent potential confounding factors when estimating the physical vs. electronic effect. See Table 1 for examples. The design of the present study, in which both physical and electronic channels operate simultaneously in a single market, ensures that none of these factors varies, affording a relatively high level of control.

Table 1 **Examples of Potentially Confounding Factors in the Typical "Physical Market A vs. Electronic Market B" Design**

Potential confounding factor	Physical market example	Electronic market example
Price discovery mechanism	Auction with soft close, e.g., the "going, going, gone" method used in traditional auctions.	Auction with hard close and fixed-price option, e.g., the method used on eBay.
Dispute resolution policy	Formal arbitration, such as that provided by the intermediary in this study for disputes between buyers and sellers.	Chance to leave feedback about other party, but no formal arbitration process.
Length of bidding window	30–60-second bidding window, typical of live, traditional auctions.	Multiday bidding window, typical of online auctions.

Note. These factors do not vary in the present study.

3. Hypotheses Development

We use buyer/seller transaction costs and quality uncertainty to motivate hypotheses about the use of the electronic and physical channels in this market.

3.1. Seller Transaction Costs and Quality Uncertainty

The seller's choice between physical and electronic presentation for each vehicle has both cost and revenue implications. The cost implications are straightforward: electronic presentation is less expensive than physical presentation, because electronic presentation eliminates the cost of transporting vehicles to the facility where the sales event is held (Kambil and van Heck 1998). The revenue implications are more complicated. The products in this market are used vehicles; thus, quality uncertainty is a potential issue. A vehicle's price achieved electronically versus physically may vary based on the degree of its quality uncertainty. First, consider a vehicle of high quality uncertainty. If the seller presents this vehicle physically, then collocated buyers can personally inspect it, which reduces the quality uncertainty. However, if the seller presents the vehicle electronically, then physical inspection is impossible and cannot be used to reduce the uncertainty. Quality uncertainty causes buyers to discount as a hedge against buying a "lemon" (Akerlof 1970, Dewan and Hsu 2004, Koppius et al. 2004). In an auction context, this suggests that buyers will either lower their bids or not bid at all, resulting in a discount. Sellers may be better off using physical presentation for vehicles of high quality uncertainty to avoid this discount, in spite of its higher cost. Next, consider a vehicle of low quality uncertainty. Buyers will not significantly discount this vehicle regardless of how it is presented, because there is little uncertainty about what they're bidding on. As a result, sellers can achieve approximately the same price for these vehicles using either presentation channel, and they will choose the electronic channel because of its lower cost.

Hypothesis 1 (H1). *The lower* (*higher*) *the quality uncertainty of a vehicle*, *the higher* (*lower*) *the probability that the seller will present it electronically*.

Hypothesis 2 (H2). *The lower* (*higher*) *the quality uncertainty of a vehicle*, *the smaller* (*larger*) *the discount associated with electronic vehicle presentation*.

This logic can be extended by considering whether buyers participate collocated or online. Online buyers

[3] An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

cannot physically inspect vehicles to eliminate quality uncertainty, regardless of how the vehicles are presented. This has two implications. First, online and collocated buyers will be asymmetrically informed and behave differently (Clemons and Weber 1997). In particular, online buyers will be at a greater informational disadvantage for vehicles of high quality uncertainty than those of low quality uncertainty. As a result, these buyers will prefer vehicles of low quality uncertainty. Second, online buyers should be less sensitive to electronic vehicle presentation than collocated buyers, because electronic presentation does not impact online buyers' ability to assess quality, whereas it does for collocated buyers.

Hypothesis 3 (H3). *The lower (higher) the quality uncertainty of a vehicle, the higher (lower) the probability that the winning bid will be placed by an online buyer.*

Hypothesis 4 (H4). *Electronic (physical) vehicle presentation is positively (negatively) associated with the winning bid being placed by an online buyer.*

If supported, H1, H2, and H3 suggest a separating equilibrium in which vehicles of low quality uncertainty are traded electronically and vehicles of high quality uncertainty are traded physically. Notice that vehicles of low quality uncertainty may be of either high or low quality in an absolute sense, i.e., known to be good or bad, with minimal uncertainty. Because this separation is based on quality uncertainty rather than absolute quality, it is not a "classic" adverse selection equilibrium ala Akerlof (1970).

3.2. Buyer Transaction Costs and Vehicle Availability

Some vehicles are more available in the market than others. For example, Chevrolet Malibus are widely available in the market, whereas Audi TTs are rare. It is more likely that a buyer can purchase a widely available vehicle at a market facility near him than a rare vehicle, which may be available at only one or two facilities throughout the country. The travel and opportunity costs associated with collocated participation at these (few) facilities may be substantial for many buyers (Watson and McKeown 1999), making the online participation channel an attractive option. This suggests that as a vehicle becomes more rare, the bidding for it will involve more online buyers, which increases the probability that an online buyer will place the winning bid.

Hypothesis 5 (H5). *The lower (higher) the availability of a vehicle in the market, the higher (lower) the probability that the winning bid will be placed by an online buyer.*

The logic supporting H5 parallels that from research on the "long tail" of electronic commerce by Brynjolfsson et al. (2003), who argued that the electronic channel in the book market permitted buyers to purchase books not available in their local geographic areas.

Buyer and seller behavior is interconnected. If H5 is supported and more of the winning bids for rare vehicles are placed by online buyers, sellers should observe this and become more likely to present rare vehicles electronically. This is because electronic presentation should be as acceptable as physical presentation to the online buyers who are purchasing these vehicles (see H4), and it is cheaper for the seller.

Hypothesis 6 (H6). *The lower (higher) the availability of a vehicle in the market, the higher (lower) the probability that the seller will present it electronically.*

4. Data

The data include all sales events between November 2003 and March 2006 in which sellers used both the physical and electronic vehicle presentation channels. There were 785 such sales events over this 29-month span for a total of 108,333 vehicles presented. Of these, 87,421 were presented physically and 20,912 were presented electronically. Of the physical vehicles, 82% (71,804) were sold, and of the electronic vehicles, 68% (14,188) were sold. In all, 78,480 vehicles were sold to collocated buyers, whose ratio of physical to electronic vehicles purchased was 5.29 to 1, and 7,512 were sold to online buyers, whose ratio of physical to electronic vehicles purchased was 3.40 to 1. Table 2 shows this data in tabular form.

4.1. Dependent Variables

The first dependent variable is ElectronicVehicle, which is a binary variable that represents whether a vehicle was presented physically (ElectronicVehicle $= 0$) or electronically (ElectronicVehicle $= 1$). The second dependent variable is Price, which is the highest bid accepted by the seller for a vehicle. The third dependent variable is OnlineBuyer, which is a binary variable that represents whether the winning bid was placed by a collocated buyer (OnlineBuyer $= 0$) or an online buyer (OnlineBuyer $= 1$). Price and OnlineBuyer are both outcomes of the auction process. If the seller does not

Table 2 Counts of Vehicles Presented and Vehicles Sold by Channel

	Physical	Electronic	Total
Vehicles presented	87,421	20,912	108,333
Vehicles sold			
to collocated buyers	65,998	12,482	78,480
to online buyers	5,806	1,706	7,512
Total	71,804	14,188	85,992

accept the high bid for a vehicle, the vehicle remains unsold and we observe neither PRICE nor ONLINEBUYER. (The high bid is not recorded in our data for unsold vehicles.) This creates a potential selection bias, which is discussed below.

4.2. Independent Variables

As discussed above, we use ELECTRONICVEHICLE as the dependent variable in an empirical model to investigate our first research question. We also use ELECTRONICVEHICLE as an *independent* variable in other models to investigate the second and third research questions. Using ELECTRONICVEHICLE as an independent variable creates potential endogeneity, which we discuss below. VALUATION represents the vehicle's value in the market at the time it was presented. The intermediary calculates and records a valuation estimate specifically for each vehicle, based on its year, make, model, mileage, and style (e.g., LX, SE), using transactions from the previous 30 days. This captures multiple vehicle characteristics as well as seasonal or inflationary trends. Thus, VALUATION is an accurate reflection of what a vehicle is worth in the market at the time it was presented.[4] VALUATION is not based on a vehicle's condition, i.e., the amount of damage or wear and tear the vehicle has sustained. Condition is controlled for separately via CONDITIONDUMMIES. The intermediary uses the condition grading scale endorsed by the National Auto Auction Association (http://www.naaa.com) to rate each vehicle on a 0–5 ordinal scale: 0 represents a poor condition, low-quality vehicle; 5 represents a good condition, high-quality vehicle. SELLERDUMMIES control for seller characteristics such as reputation, propensity to present vehicles physically or electronically, and the profile of vehicles each seller typically sells. There are 50 sellers in the data. VEHICLEAGE is calculated as the date the vehicle was presented minus January 1 of the vehicle's year. MILEAGE captures the odometer reading of the vehicle. VEHICLESUPPLY measures the number of vehicles of the same year, make, and model within the data set and represents how available (or rare) a vehicle is in the market. REOFFER is a dummy variable that denotes whether a vehicle was presented but not sold in a previous sales event. SLOT represents the order in which a vehicle was presented in a sales event. BUYERDISTANCE is the number of miles between the buyer's office and the facility hosting the sales event. NUMBERBUYERS measures the number of buyers per sales event, and PCTONLINEBUYERS is the percentage of buyers per sales event using the online participation channel. We scaled several variables by factors of 10 so that all variables were of similar magnitude to ease interpretation. The appendix lists the descriptive statistics.

4.2.1. Quality Uncertainty. The condition grading scale used by the intermediary is a quality-rating system. Prior research on rating systems indicates that extreme ratings are more informative than intermediate ratings (Fleder and Hosanagar 2007), because extreme ratings are clear signals of quality (either high or low), whereas intermediate ratings are more equivocal and convey greater uncertainty (Shardanand and Maes 1995). This suggests that vehicle condition grades on either end of the scale will convey less quality uncertainty than intermediate condition grades. An analysis of the grading scale, an excerpt of which is provided in the online supplement (available in the e-companion), indicates that this is the case. The criteria for grade 5 or grade 0 are clear and subject to little interpretation. To receive grade 5, a vehicle must be of unequivocally good quality; it can have only minor defects and require no paint or body work. To receive grade 0, a vehicle must be of unequivocally poor quality; it cannot be operable and is suitable only for scrap. The criteria for the other grades are more equivocal and represent noisier, more-uncertain quality signals. For example, a given vehicle could be classified as either grade 3 or grade 2, depending on what the grader considers a "ding" (grade 3) versus a "dent" (grade 2) and a "small scratch" (grade 3) versus a "scratch" (grade 2). The instructions for assigning intermediate condition grades also contain many equivocal terms such as "may have" and "expected to." This suggests that the relationship between quality uncertainty and condition grade is shaped like an inverted U, with extreme condition grades conveying low quality uncertainty.[5]

Using similar logic, vehicles with extreme VALUATION values may have lower quality uncertainty than vehicles with average values. The quadratic VALUATION^2 term captures this possible curvilinearity.

5. Empirical Models and Results

We estimated empirical models for each of the three dependent variables.

[4] The explanatory power of VALUATION is why the R^2 statistic in the Price model approaches 1.00.

[5] Similar inverted U-shapes with respect to uncertainty are evident in the rating systems used by other industries. In the motion picture industry, the extreme ratings ("G" and "NC-17") indicate with relative certainty whether a film is suitable for children. The intermediate ratings ("PG," "PG-13," and "R") are more equivocal and require parental judgment to resolve the uncertainty (http://www.filmratings.com). In financial markets, extreme bond ratings ("Aa" or above and "Ca" or below) provide a clearer signal of quality (or lack thereof) than intermediate ratings, which are more equivocal and subject to interpretation. We thank an anonymous referee for providing the second example.

Table 3 Results of the ElectronicVehicle Model

Independent variables	Estimate (robust S.E.)	z-statistic	Marginal effect (%)
INTERCEPT	1.378 (0.091)	15.13***	n/a
CONDITIONDUMMY_1	−0.864 (0.043)	−20.25***	−10.55
CONDITIONDUMMY_2	−1.799 (0.039)	−46.52***	−22.52
CONDITIONDUMMY_3	−2.385 (0.038)	−62.60***	−51.98
CONDITIONDUMMY_4	−2.330 (0.042)	−55.24***	−19.32
CONDITIONDUMMY_5	−2.084 (0.059)	−35.12***	−12.43
VALUATION	−0.266 (0.028)	−9.51***	−5.32 (per $10,000)
VALUATION^2	0.032 (0.006)	5.53***	0.64
MILEAGE	−0.011 (0.002)	−6.18***	−0.21 (per 10,000 miles)
VEHICLEAGE	0.076 (0.003)	23.10***	1.53 (per vehicle year)
VEHICLESUPPLY	−0.019 (0.003)	−7.02***	−0.38 (per 100 vehicles)
REOFFER	0.458 (0.018)	25.59***	11.15
SELLERDUMMIES	Available at http://www.prism.gatech.edu/~eoverby3/supplement.pdf.		

Note. $n = 108{,}333$; pseudo-$R^2 = 0.37$; log pseudolikelihood $= -33{,}193.02$.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

5.1. The ElectronicVehicle Model

Equation (1) shows the probit model designed to examine the factors that influence sellers' decisions to present vehicles physically or electronically. This model corresponds to the first research question and permits testing of H1 and H6:

$$\text{Probability}(\text{ELECTRONICVEHICLE}_i = 1 \mid X_i) = \Phi(\beta X_i). \quad (1)$$

In Equation (1), i indexes the vehicle; X_i is a vector of variables describing each vehicle, including a constant, VALUATION, VALUATION^2, five CONDITIONDUMMIES (for grades 1–5), VEHICLEAGE, MILEAGE, VEHICLESUPPLY, REOFFER, and 49 SELLERDUMMIES; β represents parameters to be estimated; and $\Phi(\cdot)$ is the standard normal cumulative distribution function. NUMBERBUYERS and PCTONLINEBUYERS are excluded because they are unknown to the seller when she makes presentation decisions. We do not include interaction terms in this or the other econometric models, because they are not central to our model development or hypothesis testing. Results, including marginal effects, appear in Table 3.

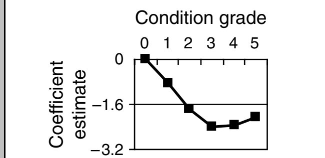
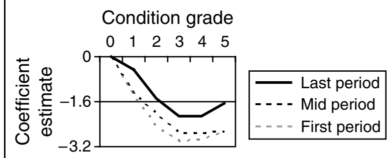
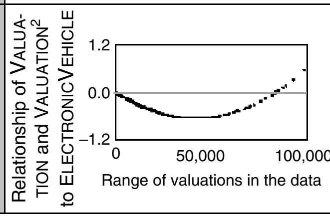
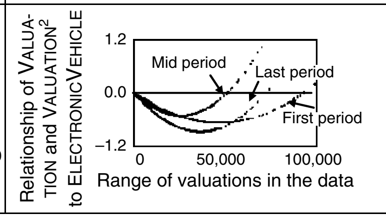
5.1.1. Testing H1. The first row and column of Figure 3 displays a plot of the CONDITIONDUMMIES coefficients reported in Table 3. Condition grade 0 represents the base case; all CONDITIONDUMMIES are significantly different from the base case ($p < 0.001$) and from each other ($p < 0.01$). According to H1, sellers should be more likely to use electronic presentation for vehicles of low quality uncertainty. This suggests that the CONDITIONDUMMIES plot should be U-shaped. The plot displays a moderate U-shape, with the coefficient for CONDITIONDUMMY_3 forming the bottom of the U. This provides some support for H1. A more-symmetric U-shape is evident with respect to VALUATION. As shown in the second row, first column of Figure 3, vehicles with small and large VALUATIONS are more likely to be presented electronically than vehicles with intermediate VALUATIONS. This U-shape reflects the negative VALUATION coefficient and the positive VALUATION^2 coefficient shown in Table 3 and provides additional support for H1.

The second column of Figure 3 illustrates how these relationships evolved over time. To investigate changes over time, we ordered the observations chronologically and divided the data into three time periods, each containing one-third of the observations. We then refitted the model for each time period and plotted the resulting coefficient estimates. The U-shape in the plot of the CONDITIONDUMMIES coefficients is more pronounced in the last period due to a greater propensity for sellers to use electronic presentation for grade 5 vehicles.[6] The results over time for VALUATION indicate that the U-shape is shallowest in the first period and more pronounced in the middle and last periods.[7] This indicates that support for H1 increased over time, as sellers gained experience with the electronic channel.

[6] All CONDITIONDUMMIES, VALUATION, and VALUATION^2 coefficients are significantly different from zero ($p < 0.05$) in each time period. All CONDITIONDUMMIES are significantly different from each other ($p < 0.05$) in each time period, except for CONDITIONDUMMIES 3 and 4 in the second period, CONDITIONDUMMIES 2 and 5 in the third period, and CONDITIONDUMMIES 3 and 4 in the third period.

[7] The VALUATION coefficients from the middle and last periods are not statistically different from each other, nor are the VALUATION^2 coefficients. All other CONDITIONDUMMIES, VALUATION, and VALUATION^2 coefficients are statistically different from each other ($p < 0.05$) across time periods, with the exception of CONDITION_1 for the first and middle periods, CONDITION_4 for the first and middle periods, and CONDITION_5 for the first and middle periods.

Figure 3 Graphical Illustration of the Relationship Between the ConditionDummies and Valuation (Including Valuation^2) and the Probability That a Vehicle Will Be Presented Electronically

	Results for entire sample	Results by time period
Plot of coefficient estimates for each of the Condition-Dummies		
Relationship of Valuation (including Valuation^2) to ElectronicVehicle for the range of Valuation values in the data.		

5.1.2. Testing H6. The coefficient for VehicleSupply in the model is negative and significant, indicating that the more available a vehicle is in the market, the *less* likely it is to be presented electronically. This indicates that sellers are *more* likely to present rare vehicles electronically, supporting H6.

Figure 4 illustrates that this relationship emerged over time. The first column shows the VehicleSupply coefficient for each of the three time periods discussed above. The second column shows the VehicleSupply coefficients recovered from a moving window regression procedure (Brown et al. 1975). This procedure complements the time period analysis by providing a more continuous view of how effects evolved over time. In this procedure, we ordered the observations chronologically, specified a window size $k = 20{,}000$ and a step size $m = 3{,}000$, and fitted the model on a moving window basis as follows. The first window contained observations 1 to k (e.g., 1 to 20,000), the second window contained observations $1 + m$ to $k + m$ (e.g., 3,001 to 23,000), and so on. This resulted in 31 windows within which we fitted the ElectronicVehicle model. Figure 4 shows a plot of the VehicleSupply coefficient recovered from these windows, ordered chronologically. The large squares represent the coefficient estimates, and the small triangles represent 95% confidence intervals. Results indicate that the VehicleSupply coefficient was usually insignificant or positive early in the data set, but shifted to become negative later in the data set. We discuss this finding, along with complementary findings for H5, more fully in §6.

5.2. The Price Model

The ElectronicVehicle model provides insight into sellers' choices between physical and electronic presentation; the Price model permits examination of how these choices affect vehicle price. This model corresponds to the second research question and permits testing of H2.

ElectronicVehicle is endogenous in the Price model, because a seller's decision to present a vehicle physically or electronically may depend at least partly on unobserved variables that also affect Price. The Price model may also suffer from a selection bias, because we only observe Price for vehicles that sellers chose to sell. We addressed both of these issues by using a variant of the Heckit procedure (Heckman 1979), which appears as Equations (2) and (3). These equations comprise the Price model:

$$\text{Price}_{i,j} = \alpha(\text{ElectronicVehicle}_{i,j}) + \beta X_{i,j} + \gamma W_j + u_{i,j} \ (\text{ElectronicVehicle is instrumented}); \quad (2)$$

$$\text{Sold}_{i,j} = 1 \quad \text{if } \delta Z_{i,j} + \zeta W_j + v_{i,j} > 0, \ 0 \text{ otherwise.} \quad (3)$$

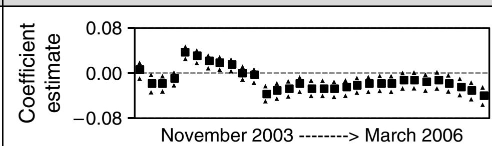
Figure 4 Examination over Time of the VehicleSupply Coefficient in the ElectronicVehicle Model

VehicleSupply coefficients per time period

	Estimate	Marginal effect
First period	0.005 (0.004)	Effect not significant
Middle period	−0.030 (0.005)***	−0.59% (per 100 vehicles)
Last period	−0.029 (0.005)***	−0.56% (per 100 vehicles)

***$p < 0.001$, robust standard errors in parentheses.

Plot of VehicleSupply coefficients from moving window regressions



Equation (2) is referred to as the outcome equation and Equation (3) as the selection equation. We discuss each in turn. In Equation (2) (outcome equation), i indexes the vehicle; j indexes the sales event; ElectronicVehicle is the focal variable whose effect we examine; $X_{i,j}$ is a vector of control variables describing each vehicle, including a constant, Valuation, five ConditionDummies (for grades 1–5), Mileage, VehicleSupply, Slot, ReOffer, and 49 SellerDummies; W_j is a vector of control variables specific to each sales event, including NumberBuyers and PctOnlineBuyers; u is an error term; and α, β, and γ are parameters to be estimated. Because ElectronicVehicle is endogenous in this model—a Hausman (1978) test rejects the null that it is exogenous with $p < 0.001$—we instrumented it using the following two variables. First, SellerElecPropensity measures the percentage of vehicles presented electronically per seller per condition grade in the 30 days prior to and including the day of each observation, not including the focal observation. For example, if a rental car company presented a condition grade 3 vehicle on May 1, 2005, the SellerElecPropensity variable for this observation is the percentage of other condition 3 vehicles the rental car company presented electronically in the 30 days prior to and including May 1. This variable is likely to be correlated with the seller's presentation decision, but not with the price of the focal vehicle. This approach is similar to the practice of using lagged levels of independent variables as instruments (Kennedy 1998). For robustness, we also used 15- and 45-day windows to calculate SellerElecPropensity. This does not affect the results. Second, we used VehicleAge as an additional instrument. The logic behind this choice is that VehicleAge is related to other vehicle characteristics such as Valuation, Mileage, and the ConditionDummies. If VehicleAge provides no explanatory power for Price beyond the other variables, then it is redundant and can be used as an instrument. Using VehicleAge as a second instrument permits the use of overidentification tests to examine instrument exogeneity.[8]

In Equation (3) (selection equation), Sold represents whether the seller accepted the high bid (Sold = 1) or not (Sold = 0). In selection model terminology, Sold = 1 means that the vehicle was "selected," because we observe the dependent variable (Price). Incorporating the selection equation allows us to test whether the relationships indicated by the Price model are biased by the seller's option to reject the high bid. In selection models, the independent variables in the selection equation should include all the variables in the outcome equation along with an additional variable that helps determine selection (Heckman 1979, Wooldridge 2002). Thus, Z in Equation (4) is a vector of variables comprised of X, the two instruments for ElectronicVehicle, and a selection variable, SellerSellPropensity. This variable is similar to SellerElecPropensity: it measures the percentage of vehicles per condition grade that each seller *sold* in the 30 days prior to and including the day of each observation, not including the focal observation. We also used 15- and 45-day windows; results are insensitive to this. v is an error term and δ and ζ are parameters to be estimated. Results of the selection equation are available in the online supplement.

To estimate the Price model, we first estimated the selection equation using all 108,333 observations via a probit model, which is standard in the Heckit procedure. Second, we used the resulting coefficient estimates to calculate the nonselection hazard, also referred to as the inverse Mills ratio. Third, we added the nonselection hazard (NonSelection) as an independent variable to the outcome equation; including this variable accounts for the potential selection bias (Heckman 1979, Wooldridge 2002). Fourth, we used two-stage least squares (2SLS) to estimate the augmented outcome equation for the 85,992 vehicles for which Price is observed. We used SellerSellPropensity, in addition to SellerElecPropensity and VehicleAge, as instruments for the endogenous ElectronicVehicle variable. This is necessary to avoid potentially incorrect exclusion restrictions (Wooldridge 2002). Readers interested in additional technical details for this procedure are referred to in Wooldridge (2002, pp. 567–568).

The unit of analysis was the vehicle. Because vehicles are grouped into sales events, we used the clustering correction developed by Huber (1967) to account for correlation among observations within sales events. Also, because the effect of ElectronicVehicle on Price is likely to vary by condition grade (as argued above), we fitted the Price model separately for the observations corresponding to each condition grade.[9] The left panel of Table 4 lists the coefficient estimates and related statistics for the observations for each condition grade, as well as for the pooled data.

[8] We also used SellerElecPropensity as a single instrument. This does not affect the results.

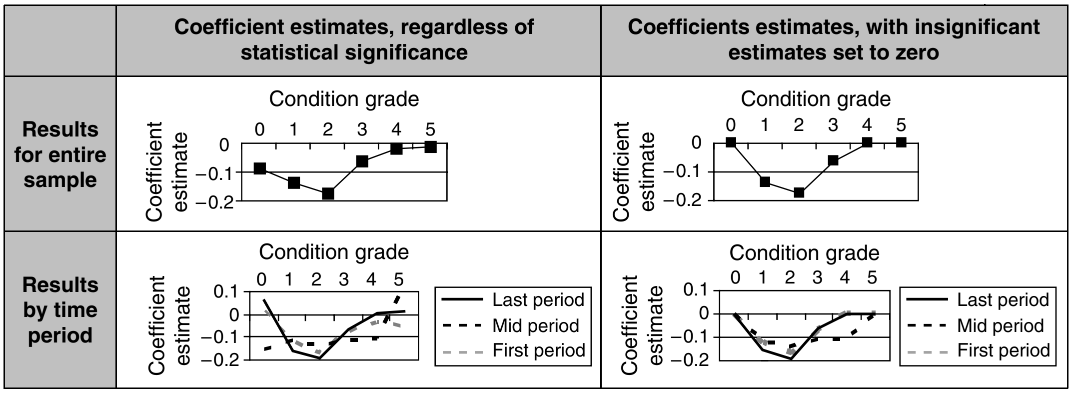
[9] An alternative method, that of interacting ElectronicVehicle with the ConditionDummies in an omnibus model, is problematic. First, each of the resulting interaction terms would be endogenous, because they contain ElectronicVehicle. Second, the ConditionDummies may interact with other variables besides ElectronicVehicle. For example, the five ConditionDummies might interact with the 49 SellerDummies if some sellers sell lower condition vehicles "as-is," whereas other sellers might stand behind them. Adding all possible interactions to an omnibus model creates a proliferation of dummy variables (many of them endogenous) and introduces needless collinearity.

Table 4 Results of the Price Model

	Heckit model, using 2SLS after selection							2SLS on the observed sample						
	Condition grade							Condition grade						
	0	1	2	3	4	5	All grades	0	1	2	3	4	5	All grades
ELECTRONIC VEHICLE (robust SE)	−0.092	−0.141	−0.175	−0.063	−0.015	0.000	−0.089	−0.090	−0.140	−0.174	−0.064	−0.017	−0.010	−0.084
	(0.059)	(0.026)***	(0.020)***	(0.020)**	(0.020)	(0.042)	(0.019)***	(0.059)	(0.026)***	(0.019)***	(0.020)**	(0.021)	(0.043)	(0.020)***
VALUATION (robust SE)	0.414	0.567	0.842	0.956	0.986	0.985	0.929	0.414	0.567	0.842	0.954	0.985	0.986	0.933
	(0.028)***	(0.020)***	(0.008)***	(0.004)***	(0.006)***	(0.012)***	(0.005)***	(0.028)***	(0.020)***	(0.008)***	(0.004)***	(0.006)***	(0.007)***	(0.005)***
MILEAGE (robust SE)	0.010	0.008	0.006	−0.004	−0.002	−0.012	0.005	0.010	0.008	0.006	−0.004	−0.002	−0.012	0.005
	(0.002)***	(0.001)***	(0.00)***	(0.001)***	(0.02)	(0.006)*	(0.000)***	(0.002)***	(0.001)***	(0.000)***	(0.001)***	(0.002)	(0.006)*	(0.000)***
VEHICLESUPPLY (robust SE)	0.001	0.003	0.003	0.001	−0.001	−0.003	0.001	0.001	0.003	0.003	0.001	−0.001	−0.003	0.001
	(0.004)	(0.002)	(0.001)***	(0.000)**	(0.001)*	(0.003)	(0.000)**	(0.004)	(0.002)	(0.001)***	(0.000)**	(0.001)*	(0.003)	(0.000)**
SLOT (robust SE)	0.010	−0.006	−0.007	−0.004	−0.003	0.001	−0.004	0.010	−0.006	−0.007	−0.004	−0.003	0.000	−0.004
	(0.003)**	(0.002)**	(0.001)***	(0.001)***	(0.003)	(0.005)	(0.001)***	(0.003)**	(0.002)**	(0.001)***	(0.001)***	(0.003)	(0.005)	(0.001)**
REOFFER (robust SE)	−0.063	−0.024	−0.036	−0.049	−0.028	−0.008	−0.061	−0.066	−0.023	−0.036	−0.055	−0.033	−0.007	−0.046
	(0.017)***	(0.013)	(0.006)***	(0.005)***	(0.008)***	(0.037)	(0.005)***	(0.014)***	(0.010)*	(0.006)***	(0.004)***	(0.006)***	(0.035)	(0.004)***
NUMBERBUYERS (robust SE)	0.007	0.036	0.032	0.015	0.014	0.005	0.026	0.008	0.036	0.032	0.015	0.015	0.007	0.025
	(0.013)	(0.002)***	(0.005)***	(0.002)***	(0.003)***	(0.015)	(0.003)***	(0.013)	(0.008)***	(0.005)***	(0.002)***	(0.003)***	(0.015)	(0.003)***
PCTONLINEBUYERS (robust SE)	0.000	0.002	−0.000	−0.001	−0.000	−0.000	−0.001	−0.000	0.002	−0.000	−0.001	−0.001	−0.000	−0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.01)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
NONSELECTION HAZARD (robust SE)	−0.010	0.003	−0.002	−0.026	−0.016	0.004	0.049	—	—	—	—	—	—	—
	(0.035)	(0.020)	(0.018)	(0.021)	(0.016)	(0.032)	(0.017)**							
F statistic for instruments [p-value]	26.83	276.72	470.84	417.31	208.67	41.51	1,309.22	38.60	414.48	620.45	597.45	288.47	44.01	1,770.55
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
J statistic for instruments [p-value]	5.17	0.72	1.59	12.79	11.66	6.55	14.61	0.38	0.68	0.01	0.03	10.33	1.31	19.05
	[0.08]	[0.70]	[0.45]	[0.00]	[0.00]	[0.04]	[0.00]	[0.54]	[0.41]	[0.93]	[0.86]	[0.00]	[0.25]	[0.00]
n (presented)	3,775	5,278	26,506	56,873	14,544	1,357	108,333	3,775	5,278	26,506	56,873	14,544	1,357	108,333
n (sold)	2,490	3,650	20,814	46,214	11,832	992	85,992	2,490	3,650	20,814	46,214	11,832	992	85,992
R^2	0.76	0.86	0.96	0.98	0.98	0.98	0.98	0.76	0.86	0.96	0.98	0.98	0.98	0.98

Note. SELLERDUMMIES for all models and CONDITIONDUMMIES for the “All grades” models available at http://www.prism.gatech.edu/∼eoverby3/supplement.pdf.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Figure 5 Plots of the ElectronicVehicle Coefficients by Condition Grade for the Price Model



5.2.1. Assessing the Possibility of Selection Bias and the Adequacy of the Instruments. The NonSelection coefficient is insignificant for each of the condition grades, indicating that selection bias is not an issue (Wooldridge 2002). NonSelection is significant for the pooled data, but including this variable has no substantive effect on the other coefficients. This indicates that the Price model can be consistently estimated using 2SLS on the observations for which we observe Price, which corresponds to estimating Equation (2) by itself using SellerElecPropensity and VehicleAge as instruments for ElectronicVehicle. The results of this specification appear in the right panel of Table 4 and are consistent with those shown in the left panel. The remainder of the discussion focuses on the results shown in the right panel.

Table 4 indicates that the instruments are adequate. They are correlated with ElectronicVehicle, but uncorrelated with the error term in the outcome equation. First, the F-statistic shown in Table 4 measures the correlation between the instruments and ElectronicVehicle. We can reject the null of zero correlation ($p < 0.001$) for each condition grade. Second, we used Hansen's J test as the overidentification test. This test measures whether the instruments are correlated with the error term as proxied by the residuals (Wooldridge 2002). We cannot reject the null of zero correlation for condition grades 0, 1, 2, 3, and 5. The only condition grade for which the null was rejected was grade 4 ($p < 0.01$). Thus, we have less confidence in the results for condition grade 4 than for the other condition grades, although based on the results for grades 3 and 5, the grade 4 results seem reasonable.

5.2.2. Testing H2. The first row of Figure 5 shows a plot of the ElectronicVehicle coefficients per condition grade.[10] The left column shows the raw coefficient estimates; the right column shows the same results but sets to zero the coefficients that are not significant (grades 0, 4, and 5). The U-shape of the plot provides support for H2. There is a statistically significant discount for electronic presentation for vehicles with intermediate condition grades, but not for those with extreme grades. This indicates that electronic presentation has no significant effect for vehicles of low quality uncertainty. Marginal effects for the ElectronicVehicle coefficients can be obtained by multiplying by 10,000 due to scaling.

The second row of Figure 5 shows the effects for each of the three time periods. The pattern of effects is U-shaped and similar throughout the 29 months of the data. The main exception is that the raw coefficient estimates for condition grade 0 and 5 vehicles are larger in absolute value in the middle time period than either the first or last time periods, as shown in the left column. However, neither of these coefficient estimates is significant, as shown in the right column.

5.2.3. Note on Buyer Participation. As noted above, we do not model individual buyers' decisions to participate collocated or online, nor do we hypothesize about how these decisions affect Price. However, we do control for the effects of buyer participation across channels in the Price model. NumberBuyers was included to control for overall participation effects, and PctOnlineBuyers was included to control for the possibility that a concentration of buyers in one of the two channels might affect Price. As shown in Table 4, NumberBuyers is positive and (usually) significant across each version

[10] We used a series of Chow tests to assess whether the coefficient estimates were different across condition grades. In each test, we pooled the observations for adjacent condition grades and tested whether the coefficients for the pooled model differed from those of the models in which each condition grade was estimated separately. Results indicate that the coefficients were significantly different between condition grades ($p < 0.01$), with the exception of grades 4 and 5. We also estimated each of the regressions for the individual condition grades simultaneously using three-stage least squares and found similar results to those reported in Table 4. Each of the ElectronicVehicle coefficients was statistically different from all others ($p < 0.05$), except for those for grades 4 and 5.

of the Price model, which is consistent with auction theory. PctOnlineBuyers is insignificant, which suggests that the mix of buyers using the online and collocated channels does not affect Price after the other variables, such as the vehicle characteristics, are accounted for.

NumberBuyers and PctOnlineBuyers could be endogenous in the Price model. For example, the weather on the day of the sales event, the mix of vehicles being presented, or the degree to which the sales event was marketed could each affect buyer participation patterns as well as Price. To account for this, we reestimated the Price model after adding dummy variables for each sales event. These EventDummies account for variables specific to the sales event that would otherwise be captured in the error term and lead to endogeneity. Their inclusion does not affect the results. Coefficients for this version of the Price model are available at http://www.prism.gatech.edu/~eoverby3/supplement.pdf.

5.3. The OnlineBuyer Model

Price is one of the observed outcomes for each sold vehicle; another is whether the winning bid was placed by an online or collocated buyer (OnlineBuyer). Equations (4) and (5) show the OnlineBuyer model designed to examine the factors that influence this outcome. This corresponds to the third research question and permits testing of H3, H4, and H5:

$$\text{OnlineBuyer}_{i,j} = \begin{cases} 1 & \text{if } \beta X_{i,j} + \gamma W_j + u_{i,j} > 0, \\ 0 & \text{otherwise;} \end{cases} \quad \text{(4 – Outcome equation)}$$

$$\text{Sold}_{i,j} = \begin{cases} 1 & \text{if } \delta Z_{i,j} + \zeta W_j + v_{i,j} > 0, \\ 0 & \text{otherwise.} \end{cases} \quad \text{(5 – Selection equation)}$$

In Equations (4) and (5), i indexes the vehicle; j indexes the sales event; $X_{i,j}$ is a vector of variables describing each vehicle, including a constant, ElectronicVehicle, Valuation, Valuation^2, five ConditionDummies (for grades 1–5), Mileage, VehicleAge, VehicleSupply, ReOffer, Slot, and 49 SellerDummies; W_j is a vector that includes OnlineBuyers and PctOnlineBuyers; $Z_{i,j}$ consists of $X_{i,j}$ plus SellerSellPropensity, which is included as the selection variable as described above; β, γ, δ, and ζ are parameters to be estimated; and u and v are error terms.

The OnlineBuyer model is similar to the Price model because the dependent variable is only observed for a subset of observations. The selection equation accounts for this potential problem. The OnlineBuyer model is different from the Price model because ElectronicVehicle is endogenous in the Price model but not in the OnlineBuyer model. The results of a Hausman test indicate that we cannot reject the null hypothesis that ElectronicVehicle is exogenous in the OnlineBuyer model ($p = 0.45$). This may be because the dependent variable in the Price model is a more strategic consideration for the seller than the dependent variable in the OnlineBuyer model. After all bids have been received, the seller should care deeply about the amount of the high bid (i.e., Price), but not as deeply about who placed it and whether he was a collocated or online buyer (i.e., OnlineBuyer). Results of the OnlineBuyer model appear in Table 5. We used the same correction

Table 5 Results of the OnlineBuyer Model

Independent variables	Estimate (robust S.E.)	z-statistic	Marginal effect (%)
Intercept	−2.331 (0.245)	−9.52***	n/a
ElectronicVehicle	0.262 (0.067)	3.90***	3.88
ConditionDummy_1	−0.158 (0.074)	−2.13*	−1.72
ConditionDummy_2	−0.167 (0.068)	−2.43*	−1.89
ConditionDummy_3	−0.107 (0.072)	−1.48	Effect not statistically significant
ConditionDummy_4	−0.044 (0.076)	−0.58	Effect not statistically significant
ConditionDummy_5	−0.049 (0.113)	−0.44	Effect not statistically significant
Valuation	0.183 (0.035)	5.24***	2.46 (per $10,000)
Valuation^2	−0.010 (0.006)	−1.55	Effect not statistically significant
Mileage	−0.011 (0.004)	−2.68**	−0.14 (per 10,000 miles)
VehicleAge	−0.016 (0.007)	−2.36*	−0.18 (per vehicle year)
VehicleSupply	0.001 (0.003)	0.35	Effect not statistically significant
Slot	0.011 (0.009)	1.26	Effect not statistically significant
NumberBuyers	0.007 (0.017)	0.39	Effect not statistically significant
PctOnlineBuyers	0.040 (0.004)	10.20***	0.51 (per percentage point)
ReOffer	0.115 (0.041)	2.78**	1.92
SellerDummies	Available at http://www.prism.gatech.edu/~eoverby3/supplement.pdf.		

Notes. $n = 108{,}333$ presented; 85,992 sold; pseudo-$R^2 = 0.15$; log pseudolikelihood $= -60{,}381.24$. We also estimated this model after including EventDummies, as described above for the Price model. Results are unaffected and are available at http://www.prism.gatech.edu/~eoverby3/supplement.pdf.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Figure 6 Plots of the Coefficients for the ConditionDummies in the OnlineBuyer Model

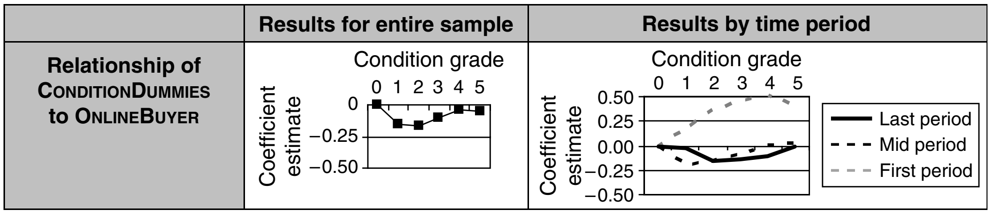


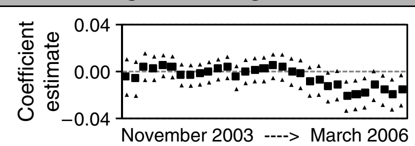
Figure 7 Examination over Time of the VehicleSupply Coefficient in the OnlineBuyer Model

VehicleSupply coefficients per time period

	Estimate	Marginal effect
First period	0.009 (0.005)	Effect not significant
Middle period	−0.003 (0.005)	Effect not significant
Last period	−0.017 (0.006) **	−0.23% (per 100 vehicles)

**$p < 0.01$, robust standard errors in parentheses.

Plot of VehicleSupply coefficients from moving window regressions



as in the Price model for the clustering of the data by sales event. See Wooldridge (2002, §17.4) for a discussion of this type of model.

5.3.1. Testing H3. The first column of Figure 6 shows a plot of the ConditionDummies coefficients reported in Table 5. Condition grade 0 vehicles represent the base case. The U-shape of the plot provides support for H3. Vehicles with extreme condition grades were more likely to be purchased by online buyers than vehicles with intermediate condition grades. All ConditionDummy coefficients are statistically different from each other ($p < 0.05$) except for ConditionDummies 1 and 2 and ConditionDummies 4 and 5. We also tested for a U-shaped relationship between Valuation (including Valuation^2) and OnlineBuyer, but found none. The coefficient for Valuation^2 was not significant ($p = 0.12$).

The second column of Figure 6 illustrates how the effects of the ConditionDummies changed over time. The pattern for the first time period is different from that for the last two periods. In the first period, vehicles with low condition grades were relatively unlikely to have the winning bid placed by an online buyer. This changed in the middle and last period, where the U-shape became apparent.[11]

5.3.2. Testing H4. The ElectronicVehicle coefficient shown in Table 5 is positive and significant, indicating that electronic presentation is positively associated with the winning bid being placed by an online buyer. This provides support for H4. This relationship does not appear to change over time, because ElectronicVehicle is positive and significant in each of the three time periods.

5.3.3. Testing H5. The VehicleSupply coefficient shown in Table 5 is insignificant, indicating that the availability of a vehicle in the market is not associated with the winning bid being placed by an online buyer. However, this overall lack of significance masks changes over time. In the first and middle time periods, VehicleSupply is insignificant. In the last period, it is negative and significant ($p < 0.01$, see Figure 7). A more continuous view of this change, produced by a moving window procedure, is shown in Figure 7. The negative relationship at the end of the time span indicates that as vehicle supply goes down—and a vehicle becomes more rare in the market—the probability that it will be purchased by an online buyer increases. Thus, there is support for H5 at the end of the time span, but not at the beginning. This result is discussed in conjunction with the result for H6 in §6.

5.3.4. A Post Hoc Test of BuyerDistance. The mean of the BuyerDistance variable was 186 miles (s.d. 333) for collocated buyers and 577 miles (s.d. 665) for online buyers. A t-test indicates that this difference is significant ($p < 0.001$). This indicates that buyers used the online channel to expand their market reach to a larger geographic area, which is consistent with the theoretical motivation for H5.

6. Discussion

Table 6 provides a summary of the research questions, hypotheses, and results. We contribute to the research literature on electronic channels in several ways.

[11] All coefficients are significant ($p < 0.05$) in the first period except for ConditionDummy_1. Only coefficients for ConditionDummies 2 and 3 are significant ($p < 0.05$) in the middle and last periods.

Table 6 Summary of Research Questions, Hypothesis Tests, and Results

Research question	Hypothesis	Supported?
Seller behavior—tested with the ElectronicVehicle model		
What influences sellers' decisions to present vehicles via the physical or electronic channel?	H1: The lower (higher) the *quality uncertainty* of a vehicle, the higher (lower) the probability that the seller will present it electronically.	Yes; effects become more pronounced over time.
	H6: The lower (higher) the *availability of a vehicle* in the market, the higher (lower) the probability that the seller will present it electronically.	Yes; effects become more pronounced over time.
Buyer behavior—tested with the OnlineBuyer model		
What influences whether the winning bid is placed by a buyer using the online channel or a buyer using the collocated channel?	H3: The lower (higher) the *quality uncertainty* of a vehicle, the higher (lower) the probability that the winning bid will be placed by an online buyer.	Yes; effects change markedly over time.
	H4: Electronic (physical) vehicle presentation is positively (negatively) associated with the winning bid being placed by an online buyer.	Yes; effects are relatively stable over time.
	H5: The lower (higher) the *availability of a vehicle* in the market, the higher (lower) the probability that the winning bid will be placed by an online buyer.	Yes; but effects do not become apparent until end of time span.
Price—tested with the Price model		
How does physical versus electronic presentation affect vehicle price?	H2: The lower (higher) the *quality uncertainty* of a vehicle, the smaller (larger) the discount associated with electronic vehicle presentation.	Yes; effects are relatively stable over time.

6.1. Consideration of Multiple, Potentially Conflicting Factors

Multiple factors, including quality uncertainty and buyer/seller transaction costs, influence use of electronic market channels. Because these factors may have conflicting effects, we consider them in concert. This contributes to a research stream in which much of the existing work has investigated individual factors, such as reduced search costs (Bakos 1997) or quality uncertainty (Koppius et al. 2004).

Our hypotheses H1 and H2 illustrate how multiple factors may affect seller behavior. Sellers can reduce their transaction costs by presenting vehicles electronically. However, this may create quality uncertainty among the buyers and lead to price discounts, particularly for vehicles whose quality is uncertain and difficult to represent electronically. This suggests that sellers should be more likely to use electronic presentation for vehicles of low quality uncertainty, which may be of either low absolute quality (e.g., known to be bad) or high absolute quality (e.g., known to be good). This in turn suggests a U-shaped relationship between absolute quality and sellers' use of electronic presentation, and absolute quality and the price discount associated with electronic presentation. The results of H1 and H2 provide support for these theoretical relationships. Multiple factors also affect buyer behavior. Buyers can lower their participation costs by using the online channel, but this eliminates their ability to inspect vehicles physically. The resulting uncertainty about vehicle quality may explain why buyers who used the online channel tended to purchase vehicles of low quality uncertainty (H3).

6.2. Interconnections Between Buyer and Seller Behavior

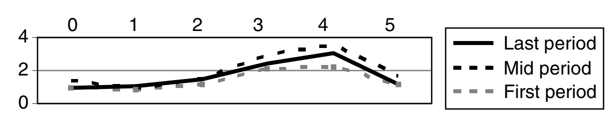
Buyers and sellers influence each other's behavior. For example, if buyers use electronic channels for one purpose but not another, then sellers observe this and adjust accordingly. We account for this interaction, and thereby complement prior work that has focused primarily on buyers (e.g., Koppius et al. 2004) or sellers (e.g., Kuruzovich et al. 2008) and does not explicitly examine the interconnections between their behavior. The results of H5 indicate that online buyers became increasingly likely to be the winning bidders for rare vehicles. Similarly, sellers of rare vehicles became increasingly likely to present them electronically (H6). It is logical for buyers and sellers to observe and respond to these behavioral patterns. For example, as sellers observe that an increasing number of rare vehicles are sold to online buyers, they should respond by presenting rare vehicles electronically. This is because electronic presentation does not impact the experience of the online buyers who purchase these vehicles, and it is cheaper for the seller.

6.3. Evolution of Effects over Time

We explored how use of the electronic channels evolved over a 2.5-year time span. Sellers became more likely over time to present grade 5 vehicles electronically, making the U-shaped relationship between absolute quality and electronic presentation more pronounced (H1). The U-shape indicating online buyers' propensity to place the winning bid for vehicles of low quality uncertainty did not emerge until the middle of the time span (H3). The relationships between vehicle availability/rarity and (a) the probability that the vehicle will be purchased by an online buyer (H5) and, (b) the probability that the seller will present the vehicle electronically (H6) became stronger over time. A plausible explanation for the time-based results is that buyers and sellers adapted to the electronic channels as they gained experience. For example, results for H3 indicate that online buyers initially shied away from condition grade 0 vehicles, but became more likely to purchase them later in the time span, perhaps because they realized that they could predict the quality of these vehicles without having to see them in person.

There are alternative explanations for the pattern of effects over time. First, it is possible that the effects might be the result of a different set of buyers and sellers using the electronic channels at the beginning of the time span than at the end. This does not appear to be the case for the sellers, because all sellers who used the electronic presentation channel in the first time period also used it in the next two periods. To determine if changes in the set of buyers might explain the effects over time, we fitted the Online-Buyer model for the middle and last time periods using only observations in which the winning buyer had also appeared in the first time period. Results are similar to those shown in Figures 6 and 7, which casts doubt on this rival explanation. Second, it is possible that the effects for H5 and H6 could be alternatively explained by changes over time in the distribution of rare vehicles across condition grades. For example, if the grade 0 and 1 vehicles in the first time period were primarily vehicles that were widely available in the market, then this could represent an alternative explanation for why online buyers did not tend to purchase them. To examine this, we plotted the mean of the VehicleSupply variable for each condition grade for each time period. As shown in Figure 8, these plots are similar for each period, casting doubt on this rival explanation. In summary, although we cannot be sure that the pattern of effects over time was the result of buyer and seller adaptation to the electronic channels, this explanation seems plausible.

Figure 8 Mean of the VehicleSupply Variable (y-Axis, Shown in Increments of 100) per Condition Grade (x-Axis) for the Three Time Periods



6.4. Limitations

The theoretical model discussed in §3 predicts a separating equilibrium in which vehicles of low quality uncertainty are traded electronically and vehicles of high quality uncertainty are traded physically. Empirically, this should manifest itself as a series of U-shaped relationships between absolute vehicle quality and (a) electronic presentation, (b) price discounts, and (c) the probability that the winning bid will be placed by an online buyer. These U-shapes are apparent in the results and become more pronounced over time, with the exception of the results related to price, which display a relatively constant U-shape over time. The change over time illustrates that effects in this or similar contexts may not manifest themselves immediately. There is likely to be an adaptation period as buyer and seller behavior reequilibrates in response to the introduction of new electronic channels.

It is possible that the adaptation period extended beyond our data, because the correspondence between the empirical results and the predictions of the theoretical model is imperfect. The U-shapes are not perfectly symmetrical; there is noise in the system. For example, theory and the empirical results indicate that sellers should present all condition 5 vehicles electronically, but many sellers present grade 5 vehicles physically. A possible explanation for this discrepancy is that many sellers store their vehicles at physical market facilities while they are being sold. These facilities are designed to store large numbers of vehicles in a secure environment, which is particularly important for high-quality vehicles that might be targets for vandalism or theft. Vehicles stored at physical facilities can be offered physically with little or no incremental cost, which may make physical presentation as rational as electronic presentation. There are likely to be other practical considerations that preclude perfect correspondence between the empirical results and the theoretical model. We expect the correspondence to continue to improve as market participants gain additional experience with the mixture of electronic and physical channels.

Another limitation is that we focus on a single product category: automobiles. This is an important product category, because approximately 25% of retail spending in the United States is on automobiles.[12] Thus, the automotive industry has significant

[12] Sales at an automotive dealership accounted for 22.9% of total U.S. retail sales in 2005 (2006 National Auto Dealers Association Data Report, p. 9 (http://www.nada.org/Publications/NADADATA/2006/default.htm)).

relevance and warrants scholarly attention. The focus on this industry creates a breadth versus depth tradeoff, however, and the ability to generalize the results to categories with dissimilar product characteristics may be limited. However, the results may generalize to other markets in which products are of uncertain quality, as well as to markets in which electronic and physical channels coexist, such as many industrial markets, markets for houses and other types of real estate, and markets for agricultural products. Some aspects of these markets will transition to electronic channels (and have already), but other aspects are likely to continue to rely on traditional physical channels. In addition, our focus on high-dollar, durable goods adds to the overall generalizability of existing research on electronic and physical market channels, which has often focused on markets for much less valuable and homogeneous products, such as books, CDs, and related consumer products.

A limitation of our data is that we do not observe individual buyer characteristics such as age, gender, computer savvy, or dealership type. It is possible that online buyers and collocated buyers differ on these or other demographic dimensions. The results of the OnlineBuyer model could be driven by these differences, rather than by the hypothesized factors. To examine this, we reestimated the OnlineBuyer model after restricting the sold vehicles in the model to only those purchased by buyers who used both the online and collocated channels. These results are similar to those presented in Table 5, which indicates that the results are more likely due to the hypothesized factors than to systematic differences between online and collocated buyers. Also, a post hoc analysis revealed that 64% of the buyers in the sample who used the online channel also used the collocated channel, casting further doubt on the possibility that differences in buyer characteristics are responsible for the results.

7. Conclusion

In this study, we investigated how buyers and sellers used a mixture of electronic and physical channels over a 2.5-year period in a market for products of uncertain quality. Although the market intermediary used a standardized grading scale to reduce the quality uncertainty, the grading scale did not eliminate it. Instead, the effect of the scale was to segment the market into vehicles of relatively low quality uncertainty, which are those that are in either very good or very bad condition, and vehicles of higher quality uncertainty, which are the "average" condition vehicles for which quality is more wide-ranging.

Our results indicate that buyers and sellers tended to use the electronic channels to trade vehicles of low quality uncertainty and those that are relatively rare. They used the physical channels to trade vehicles of high quality uncertainty and those that are relatively common. For example, sellers were as much as 50% more likely to use electronic presentation for vehicles of low quality uncertainty than for those of high quality uncertainty. This is because electronic presentation is cheaper than physical presentation, and there is no associated price discount for vehicles of low quality uncertainty. On the other hand, electronic presentation of a vehicle of high quality uncertainty was associated with a significant discount, usually around $600, which may explain why sellers tended to present these vehicles physically. These patterns became clearer over time as buyers and sellers adapted to the electronic channels.

The results indicate that the electronic channels have had important effects on how buyers and sellers conduct transactions and the price at which vehicles are traded. However, the introduction of the electronic channels has not caused buyers and sellers to abandon the legacy physical channels. Thus, the appropriate question about the evolution of this market is not "when will the market shift to electronic trading," but rather "what aspects of the market will shift to electronic trading." Multiple factors interact to influence buyer and seller use of physical and electronic channels, including quality uncertainty; transaction costs related to search, travel, and presentation costs; and the behavior of the other party to the transaction. Use of electronic channels may also evolve over time as buyers and sellers gain experience. From a research perspective, it is important to consider each of these factors, because cross-sectional studies that use a single theoretical lens to investigate how either buyers or sellers use a new market channel may not capture the complexity of market behavior. From a managerial perspective, market designers should consider the nature of their markets and the products exchanged (e.g., are products of uncertain quality, are products unevenly distributed geographically) when deciding the appropriate mixture of electronic and physical channels to provide.

Advances in information technology will continue to change how markets operate. As new electronic channels are implemented, this and related research will help us better control and predict their success and provide insight into how market participants will react.

8. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

Appendix. Description of Variables

Variables	Descriptive statistics
ElectronicVehicle	ElectronicVehicle = 0, n = 87,421; ElectronicVehicle = 1, n = 20,912.
Price	Mean = 9,710 (s.d. 7,655); Range: 25 to 148,000. Variable scaled by dividing by 10,000.
OnlineBuyer	OnlineBuyer = 0, n = 78,480; OnlineBuyer = 1, n = 7,512.
Sold	Sold = 0, n = 22,341; Sold = 1, n = 85,992.
Valuation	Mean = 10,349 (s.d. 7,530); Range: 25 to 151,000. Variable scaled by dividing by 10,000.
ConditionDummies	See Table 4 for counts by condition grade.
SellerDummies	There are 50 sellers in the data set.
VehicleAge	Measured in years. Mean = 4.21 (s.d. = 3.46); Range: −0.47[a] to 46.18 (1.8% are over 15 years old).
Mileage	Mean = 60,739 (s.d. 47,939); Range: 0 to 973,066 (1.2% of vehicles exceed 200,000 miles). Variable scaled by dividing by 10,000.
VehicleSupply	Mean = 198.04 (s.d. 304.58); Range: 1 to 1,362. Variable scaled by dividing by 100.
ReOffer	ReOffer = 1, n = 10,630; ReOffer = 0, n = 97,703.
BuyerDistance	Mean = 221.32 (s.d. 390.29); Range: 0 to 3,294.
NumberBuyers	Mean = 55.92 (s.d. 49.35); Range: 2 to 372. Variable scaled by dividing by 100.
PctOnlineBuyers	Mean = 7.05% (s.d. 8.55%); Range: 0 to 67.57%. Variable scaled by dividing by 10.
Slot	Mean = 95.92 (s.d. 111.09); Range: 1 to 1,269. Variable scaled by dividing by 100.
SellerElecPropensity	Mean = 0.19 (s.d. 0.29); Range: 0 to 1.
SellerSellPropensity	Mean = 0.79 (s.d. 0.22); Range: 0 to 1.

Notes. The correlation matrix is available in the online supplement, and information about how the variables change over time is available at http://www.prism.gatech.edu/~eoverby3/supplement.pdf.
[a]A 2005 model vehicle offered in 2004 would have a negative age.

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