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ABSTRACT

This paper addresses the question of how much the Internet lowers prices for new cars and why. Using a large dataset of transaction prices for new automobiles and referral data from Autobytel.com, we find that online consumers pay on average 1.2% less than do offline consumers. After controlling for selection, we find that using Autobytel.com reduces the price a consumer pays by approximately 2.2%. This suggests that consumers who use an Internet referral service are not those who would have obtained a low price even in the absence of the Internet. Instead, our finding is consistent with consumers choosing to use Autobytel.com because they know that they would do poorly in the traditional channel, perhaps because they have a high personal cost to collecting information and bargaining. This group disproportionately uses Autobytel.com because its members are the ones with the most to gain. We estimate that savings to consumers who use Autobytel.com alone are at least $240 million per year. Since there are other referral and informational sites that may also help consumers bargain more effectively with dealers, we conclude that the Internet is facilitating a large transfer of surplus to Internet consumers in the retail auto industry.

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1 Introduction

From the time the Internet started to be used for commercial applications, much attention has centered on predictions that, while the Internet would introduce new business opportunities for some firms, it would substantially lower the profitability of many firms. These predictions were based on economic and marketing theories which show that the more easily customers can obtain information about prices and products, the lower seller's profitability will be, either through market forces of competition or because customers will have better negotiating positions. The most prevalent method of studying these predictions has been to compare market outcomes in online and offline markets.

An area that has received much less attention is how the Internet affects offline transactions in established industries. Transactions need not occur online in order to be affected by the fact that the Internet makes price and product information more easily available, and that new Internet institutions change the way that price negotiation is conducted.

An excellent illustration of this is the auto industry, one of the largest and most important industries in the US. By regulation, retail sales of new automobiles must be made by local dealers, not by manufacturers or third parties. Most automobile dealers sell cars by negotiating prices individually with each customer. As a result, identical cars can sell for prices that differ by hundreds, or even thousands, of dollars. Dealership profits would therefore be dramatically reduced if all customers paid the lowest price a dealer is willing to agree to. The Internet has made possible easily accessible third party "infomediaries," which purport to enable customers to obtain just such prices. Not surprisingly, given the magnitude of consumers' average expenditure and the confrontational nature of the purchase process, infomediaries have become popular in the automotive industry. In 2000, according to J.D. Power and Associates (2000b), 48% of new car buyers visited at least one independent vehicle site such as Autobytel.com, Carpoint.com, Edmunds.com, ConsumerReports.com, and KelleyBlueBook.com.

The question this paper addresses is whether such infomediaries can lower prices – and perhaps profits – in an established offline industry. In particular, we examine evidence that Internet referral services causally lower prices for retail auto sales. This paper begins where Scott Morton, Zettelmeyer, and Silva-Risso (2001) left off. In that paper we showed that consumers in California who used such a service paid on average 1.5% less, controlling for the car purchased, than traditional consumers. However, that finding appears at first blush to say more about whether the Internet lowers car retailers' profitability than it really does. This is because, holding cost constant, profits in the car industry will have been changed by the Internet only if the Internet has changed the *distribution* of prices. Just because Internet consumers are paying less than offline consumers does not mean that they are paying less than they would if the Internet did not exist. Disproportionate movement of good bargainers to the Internet, the "cowboys" of our title, would generate unequal prices in the two channels, and lower prices in the Internet channel, without changing the price any given individual pays. Instead, if Internet referral services are used disproportionally by those who are averse to comparison shopping and haggling, the "cowards" of our title, then the Internet is aiding these consumers in obtaining lower prices than they would receive offline. In this latter case, the Internet has a real effect on the distribution of prices, and hence the division of surplus in car retailing.

To obtain an estimate of the causal effect of Internet referral services on car prices, we control for potential selection effects with instrumental variables. In addition to estimating the 'treatment' effect of Internet referral services on the prices paid by online consumers, this approach also allow us determine which types of consumers are disproportionally likely to use the Internet for car buying. We supplement this statistical approach with a consumer survey in which we ask consumers directly about the unobserved variables which we believe may lead to selection effects. This allows us to test directly for a correlation between these variables and reported Internet use.

We answer these research questions by analyzing transaction data on over 600,000 new car purchases nationwide in combination with referral data from Autobytel.com. Autobytel.com is an independent Internet referral service that offers consumers detailed information about individual cars, including current market conditions and invoice pricing. Autobytel.com also has contractual relationships with approximately 5,000 of the 22,000 US dealerships (in Q1, 2001) which are designed to help Autobytel.com users get good prices for their cars. From the website, a consumer may submit a free purchase request that is forwarded to one of Autobytel.com's contracting dealers. The dealer then responds with a price offer which is supposed to be the lowest price the dealer would generally offer in the showroom.

We find that consumers who use Autobytel.com pay on average 0.9% less than traditional buyers for an identical car. However, after instrumenting for Autobytel.com usage, our estimate of the causal effect of the Internet on price, compared to the traditional channel is approximately 2.4%. (Purchasing from an Autobytel.com affiliated dealer, regardless of what channel was used to buy the car, results in price that is lower by about 1%.) The increase in the magnitude of the Autobytel.com coefficient between the two specifications suggests that consumers who use an Internet referral service are those who are poor at bargaining in the traditional channel. This may be due to a lack of bargaining skill, or an aversion to (or high cost of) engaging in protracted face-to-face negotiation.

While these results suggests that consumers who consider themselves disadvantaged in the traditional face-to-face bargaining process are more likely to use the Internet, we cannot test this conclusion directly with our large dataset of transactions because the data lacks measures of consumers' cost of bargaining or searching. Therefore we have collected a second set of data which contains measures of whether individuals perceive themselves to be poor bargainers and whether they are time constrained in negotiating for a new car. We find that consumers who expressed a high disutility of bargaining and lack of time were more likely to use the Internet. It seems that these consumers are sufficiently aware of their bargaining disadvantage that they choose to use the Internet as a way to improve their bargaining outcome. These results confirm our conjecture from our instrumental variables estimation, namely that it is the "cowards," not the "cowboys" who are disproportionately likely to use the Internet.

We conclude from the combination of our results that the Internet, by aiding some consumers in obtaining lower prices than they would have received offline, has had – at the time of our study – a real effect on the division of surplus in car retailing. We hesitate to draw conclusions about the long run equilibrium in this industry, since our data are for 1999, a relatively early year for Internet referral services. Our analysis focuses on the early adopters of this technology, and assumes that this small group has not yet caused changes in the remainder of the industry – such as new offline equilibrium prices and dealer exits.

We also find that consumers who purchase at the Autobytel.com dealer to whom they were referred pay, on average, nearly the same as consumers who switch to another dealer ($32 less for switchers). While this suggests that the information provided by Autobytel.com is portable, it also suggests that consumers, on average, benefit only a very small amount from switching away from the referral dealer. Further, we compare the prices paid by online consumers who obtained a referral for the specific make and model that they purchased with the prices paid by online consumers who requested a referral for a car different from the one they ultimately bought. The group that obtained information on the product purchased paid about 1% less than offline consumers; the group that obtained information on a different product from the one purchased paid 0.5% less than offline consumers. This suggests that having a make- and model-specific price quote has a bigger effect on the price a customer pays than does general information that might be obtained using the Internet. It also suggests that information drives prices, not individual characteristics associated with Internet usage. This finding is also consistent with our previous result, namely that the mere fact that a consumer has chosen to use the Internet in searching for a new car cannot explain the lower prices Autobytel.com consumers obtain.

This paper contributes to a small body of empirical literature analyzing the effect of Internet institutions such as referral services and shopping agents on firms' product market behavior. Brynjolfsson and Smith (2000), Ellison and Ellison (2004), and Iyer and Pazgal (2003) analyze the effect of comparison shopping agents on firms' pricing strategies. Brown and Goolsbee (2002) shows that the Internet may have helped to lower prices for term life insurance. In a recent theoretical paper, Chen, Iyer, and Padmanabhan (2002) analyze "referral infomediaries" and argue that referral services help retailers price discriminate and that referral infomediaries should contract only with a subset of retailers. Scott Morton, Zettelmeyer, and Silva-Risso (2001) is the precursor to this paper – we begin where that paper ends. That paper documents differences in online vs. offline pricing of new cars, however, it does not address selection, rent redistribution, or the effects of competition. In particular, Scott Morton, Zettelmeyer, and Silva-Risso (2001) does not estimate the 'treatment effect' of referral infomediaries nor does it answer which types of consumers are most likely to use the Internet. Finally, that paper only had data from California, whereas the present paper relies on a national sample.

We proceed as follows. In section 2, we discuss why an Internet referral service may change vehicle prices. In section 3, we discuss our national transaction dataset. Section 4 is a comparison of online and offline prices for cars. We also examine how the price paid by Autobytel.com users varies with level of competition in the retail auto market. In section 5, we control for selection and derive the average savings that result from using Autobytel.com. We also estimate consumers' probability of using the Internet with a second set of data which includes measures of consumer traits. Section 6 is an analysis of which aspect of a referral enables consumers to obtain a lower price. Section 7 concludes the paper.

2 The effect of Internet referral services on prices

A consumer who submits a purchase request on an Internet referral service provides her name, address, contact information, and the type of car she is looking for. The dealership contacts the consumer within 48 hours (often much sooner) with a "fixed" price.[1] In this way, a consumer may purchase a car without setting foot in the dealership until she picks up the vehicle. Autobytel.com assigns dealers an exclusive territory; any leads generated within that territory are passed on to the dealer in exchange for a dealer subscription fee. Dealers pay an annual fixed fee based on the size of the dealership, on average $1607/month. Since the closing ratio (sales/referrals) is about 13% for Autobytel.com, dealers pay on average $135 per sold vehicle to Autobytel.com.[2]. In this section, we discuss several reasons for which Internet referral service users might pay prices different from those paid by traditional consumers.

[1] According to J.D. Power and Associates (2000a), 42% of dealerships claim that their initial price contains no room for further negotiation. 42% give discounts but leave room for negotiation. 14% will quote a discounted price only if the customer insists by e-mail or phone. 2% of dealerships don't give discounted price until the consumer comes to the dealership.

[2] Youngme Moon (1999), "Autobytel.com," HBS Case Study, and J.D. Power and Associates (2000a)

2.1 Possible reasons for offline vs. online price differences

There are several different, not necessarily mutually exclusive, reasons that online prices may be lower than offline prices.

Online consumers are better informed: The higher quality and lower price of online information may lead consumers to consume more information than they would have offline. Consumers who are better informed about market prices, the characteristics of their preferred cars, and negotiation strategies may be better armed to bargain with the dealer and thus receive, on average, a lower price. Better information is likely to be particularly important because prices for cars are individually negotiated, instead of being posted.

Bargaining on behalf of consumers: The contract between the Internet referral service and the dealer contains incentives that may cause the dealer to offer referred customers low prices. While an Autobytel.com dealer may decide whether and how to convert each lead into a sale, the service expects a substantial proportion of leads to result in a sale.[3] If the percentage of referrals "closed" (sales/referrals) is too low, the dealer may be terminated by the Internet referral service and replaced by another dealer in that area. Provided the stream of customers generated by the Internet referral service is valuable to the dealership, it has an incentive to quote prices low enough to keep its "close" percentage sufficiently high. In a sense, the referral service bargains on behalf of a group of consumers, although that group is not yet formed. Autobytel's bargaining is effective partially because the consumers in the group are incremental to the dealership.[4]

Salesperson compensation: Autobytel.com stipulates in its contracts that the "Internet salesperson" at a dealership should handle only Internet referrals and not "walk-ins." Also, this salesperson is supposed to be compensated on sales volume rather than on margin. This encourages the Internet salesperson to focus on closing additional sales rather than on maximizing unit profits.[5] However, both dealers and managers at Autobytel.com reported inconsistent compliance among dealers with Autobytel.com's rules.

Lower selling cost: It is possible that an Internet sale is less costly to carry out than a conventional sale. Online buyers may be low cost because they have searched already (perhaps

[3] Autobytel.com monitors this with customer satisfaction surveys. These surveys are the only way the referral service knows if its customers are receiving the service they expected.

[4] Autobytel.com dealers have told us that they consider the subscription fee to be a kind of dealer advertising; the cost of attracting one customer using Autobytel.com is less than that of using traditional advertising.

[5] We would expect this practice itself - regardless of the Internet - to lead to lower prices. However, it would presumably be much more effective for a given dealership to implement it in conjunction with an increase in consumer traffic. In this way, the salesperson's total compensation and hours worked remain high. The low price/high volume strategy can be more effectively undertaken through business stealing via the Internet in conjunction with a change in sales staff compensation.

test-driving at another dealership), have decided what car they want, and are ready to buy. Therefore, the dealer may be able to spend less time selling and haggling. Because Internet sales typically are performed by an “Internet Sales Department” with profit and loss responsibility separate from conventional sales, we would expect that lower costs in that department might translate into lower equilibrium prices for cars sold to Internet customers.

Lower cost dealerships: In addition, consumers may gain from shopping online even if Internet referral services do not cause dealers to offer different prices to online and offline consumers. This is because referral services may simply sign up the lowest-cost/lowest-price dealers in each region. In this way a consumer gains by using the service because she does not have to search for the cheapest dealership in her area.

There is also an argument for why consumers who use referral services may pay more than other consumers.

Online consumers are less price sensitive: Internet referral services are convenient because they allow a consumer to engage in the car purchase process at any time of day or night without leaving her home. In addition, referral services reduce consumers’ direct interaction with dealers. To the extent that consumers with a high utility for convenience are less price sensitive, we should expect that dealers charge referral customers higher prices—not lower prices as claimed by Internet referral services.

2.2 Selection

Even if we observe that average online prices are lower than average offline prices, it could still be the case that a referral site has no effect on the price a particular consumer receives. Suppose that Autobytel.com consumers would have obtained information from books and friends in the absence of the Internet, or that these are customers who are already good bargainers (“cowboys”). Then Autobytel.com might simply substitute for other information sources and mechanisms which existed before the advent of the Internet; consumers could be paying the same prices they would have without the Internet, but because these consumers disproportionately use the Internet, Internet prices are lower than average.

Note, however, that the selection effect could also work in the opposite direction from that just described. Suppose that Autobytel.com users have a high personal cost to collecting information and bargaining. Such consumers know that they will pay a relatively high offline price for a car because they find it costly to, for example, comparison shop and haggle (“cowards”). If so, they will benefit more than will an average buyer from a service that provides information and “bargains” on their behalf. This may cause them to be more likely to use Autobytel.com.

Notice that if the consumers who use Autobytel.com are not a random sample of the population, we can infer whether it is the 'cowboys' or 'cowards' who choose to use the Internet from whether the estimated coefficient on Internet usage rises or falls when moving from a specification that does not control for selection (OLS) to a specification that does (IV). This inference also indicates whether the Internet has a real effect on the division of surplus in car retailing. For example, a drop in the estimated Autobytel.com coefficient when moving from OLS to IV implies both that the causal effect of the Internet is negative, and that consumers who use Internet referral services would have paid above average prices had they not used the Internet. We can conclude that the Internet has redistributed surplus from dealers to customers. If controlling for selection increases the estimate of the average price paid by a referred consumer to zero, then consumers who use Internet referral services are simply "savvy bargainers" and Autobytel.com has no causal effect on the distribution of surplus in car retailing.

3 Data

Our data come from a major supplier of marketing research information (henceforth MRI) and Autobytel.com. MRI collects transaction data from a sample of dealers in the major metropolitan areas in the US. We have data containing every new car transaction at these dealerships from January 1, 1999 to February 28, 2000.[6] These data include customer information, the make, model and trim level of the car, financing information, trade-in information, dealer-added extras, and the profitability of the car and the customer to the dealership.

We add to these data information on whether a consumer submitted a purchase request using Autobytel.com during 1999. We consider a match between observations from Autobytel.com and MRI when either the geocoded address or the phone number associated with the referral and the purchase transaction are the same. Each observation in the new dataset is a transaction from the MRI data, augmented by the information from the Autobytel.com data if there was a match.[7] We define four variables that measure Internet usage and subsequent purchase decisions. The first variable is an indicator variable for an Autobytel.com customer (*Autobytel*), which marks whether the customer who purchased the car submitted a purchase request using Autobytel.com. The unit of observation is a transaction, not a referral, and this variable is equal to 1 for any customer who requested a referral, whether or not the transaction

[6] We include an additional two months of transaction data to capture consumers who asked for a referral in 1999 but did not finalize the transaction until 2000. While most referrals result in transactions within a few days, some take longer. For example, some consumers ask for referrals for multiple cars over time before buying a vehicle.

[7] We cannot analyze the purchase choices of non-matching Autobytel.com customers as we do not know whether they purchased a car and if they have, what car they purchased.

was at the dealership to which the customer was referred. The second variable we create is an indicator variable for an Autobytel.com franchise dealer (*AutobytelFranchise*), which indicates whether the dealer that sold the car is an Autobytel.com affiliated dealer. Affiliation means that the dealer is under contract with Autobytel.com and receives purchase requests. The third indicator is *SameDealer* and marks cases in which the dealer that sold the car is the same dealer to which the purchase request was submitted. Note that *SameDealer* can equal 1 only if *Autobytel=1.* The final indicator variable, *ChangeCar*, marks whether the make and model an Autobytel.com user bought differs from the make and model for which she obtained a referral. Autobytel.com was the leading Internet referral service in 1999 with slightly over 2 million referrals.[8] However, since there are online referral services other than Autobytel.com, the customers in the combined dataset who are not identified as using Autobytel.com may have used one of its competitors. This biases our empirical result against finding lower prices for Internet users since we will be comparing a group that used Autobytel.com with a group that may include users of competing services.

Within the group that used Autobytel.com, about half of consumers buy a make and model for which they did not request a purchase referral. For most of the results that follow, we restrict ourselves to observations in which an Autobytel.com user purchased a make and model for which she requested a referral.[9] Restricting ourselves to these consumers who are informed about the car they buy makes for the cleanest comparison between more informed Autobytel.com users and less informed non-users. Thus, the main dataset, results, and summary statistics exclude the consumers who buy a make and model different from the one they requested. Later in the paper we return to considering the remaining Autobytel.com consumers. After dropping observations with missing data, our main dataset has 620,641 transactions at 3514 dealerships. Summary statistics are in the Appendix.

3.1 Dependent variable

The price observed in the dataset is the price that the customer pays for the vehicle including factory installed accessories and options and the dealer-installed accessories contracted for at the time of sale that contribute to the resale value of the car.[10] The *Price* variable we use as

[8]Autobytel.com had between 45 and 50% market share of online car shopping in 1999 (LA Times, 3/28/2000, “Mergers and Acquisitions Report,” Securities Data Publishing 6/12/2000). According to J.D. Power and Associates (2000b), Autobytel.com is the most visited purchase referral site. It is visited by 33% of consumers that researched online to shop for a car, followed by Autoweb.com (18%), and Carpoint.com (17%).

[9]For those consumers who ask for multiple referrals, we consider that they are informed about the car they buy if any one of their referral requests matches the purchased car.

[10]Dealer-installed accessories that contribute to the resale value include items such as upgraded tires or a sound system, but would exclude options such as undercoating or waxing.

the dependent variable is this price, minus the *ManufacturerRebate*, if any, given directly to the consumer, and minus what is known as the *TradeInOverAllowance*. *TradeInOverAllowance* is the difference between the trade-in price paid by the dealer to the consumer and the estimated wholesale value of the trade-in vehicle (as booked by the dealer). We adjust for this amount to account for the possibility, for example, that dealers may offer consumers a low price for the new car because they are profiting from the trade-in.

3.2 Controls

We control for car fixed effects. A "car" in our sample is the interaction of make, model, body type, transmission, displacement, doors, cylinders, and trim level. This leaves 834 thus-defined cars after dropping cars with fewer than 300 sales. We exclude these data because the smaller number of observations limits what we learn from these cars and because we want to be able to estimate car fixed effects. While our car fixed effects will control for most of the factors that contribute to the price of a car, it will not control for the factory- and dealer-installed options which vary within trim level. The price we observe covers such options but we do not observe what options the car actually has. In order to control for price differences caused by options, we include as an explanatory variable the percent deviation of the dealer's cost of purchasing the vehicle from the average vehicle cost of that car in the dataset. This percent deviation, called *VehicleCost* will be positive when the car has an unobserved option (for example a CD player) and is therefore relatively expensive compared to other examples of the same car as specified above. The measure also takes into account any variation in holdback and transportation charges.

To control for time variation in prices, we define a dummy *EndOfMonth* that equals 1 if the car was sold within the last 5 days of the month. A dummy variable *WeekEnd* specifies whether the car was purchased on a Saturday or Sunday to control for a similar, weekly effect. In addition, we introduce dummies for each month in the 14 month sample period to control for other seasonal effects and for inflation. If there are volume targets or sales on weekends, near the end of the month, or seasonally, we will pick them up with these variables.

We control for the number of months between a car's introduction (as a new model) and when it was sold. This proxies for how new a car design is and also for the dealer's opportunity cost of not selling the car. Judging by the distribution of sales after car introductions, we distinguish between sales in the first four months, months 5-13, and month 14 and later and assign a dummy variable to each category.

We control for the competitiveness of each dealer's market. For each dealership we count the number of dealerships with the same nameplate that fall in a zip code that is within a 10 mile radius of the zip code of the focal dealership. We control for cases where one owner owns several franchises, by counting only the number of separately-controlled entities.

We also control for many demographic variables (such as income, education, occupation, race, etc.) of buyers by using census data that MRI matches with the buyer's address from the transaction record. The data is on the level of a "block group," which makes up about one fourth of the area and population of a census tract. On average, block groups have about 1100 people in them. Finally, we control the region in which the car was sold.

3.3 Summary statistics

We present descriptive statistics by whether a consumer used Autobytel.com to get a price quote for the make and model car they purchased. Table 1 on page 32 shows that 3.1% of the buyers in the sample used Autobytel.com, while 24% of the cars in the sample are sold at dealerships that have a contract with Autobytel.com.[11] Of consumers in the sample, 40% trade in a vehicle, and 75% obtain some amount of dealer financing. About 36% of customers are female, and the average age of all buyers in the sample is 44. Among consumers who used Autobytel.com, 28% buy from the dealer they were referred to (see Table 2). The average price of the cars bought by Autobytel.com consumers is slightly higher and their *TradeInOverAllowance*, the amount the dealer subsidizes the trade-in, is considerably lower. The gross profit margin does not differ greatly between online and offline sales. The average offline car earns a dealer $1438 compared to $1382 for a sale through Autobytel.com.

Autobytel.com affiliated dealers are clearly different from others (see Table 3). They are larger, fewer of their sales involve a trade-in vehicle, and they are located in areas that are slightly more competitive. Autobytel.com franchises have customers who are from higher income neighborhoods, but on average, they serve people from minority census tracts as often as other dealerships. The average age of customers at the two types of dealerships is similar.

4 Price Estimation

Our primary interest is whether use of Autobytel.com alters the average price a consumer pays for her car. In this section we use a standard hedonic regression to estimate whether Autobytel.com users pay different prices than other consumers. In the next section we control for selection and contrast the OLS and IV results. We follow the hedonic pricing literature (for example Fisher, Griliches, and Kaysen (1962)) and work with $\ln(Price)$ as our dependent

[11] This proportion of Autobytel.com users approximately doubles if one includes those who purchase a car different from the one for which they requested a purchase referral.

variable.[12] We estimate the following specification:

$$\ln\left(Price_i\right) = \alpha_1 Autobytel_i + \alpha_2 AutobytelFranchise_i + \beta X_i + \epsilon_i$$

The X matrix is composed of transaction and car variables: car, month, and region fixed effects, controls for model recency, whether the consumer traded in a vehicle, and car cost.

4.1 Full sample results

Prices paid by Autobytel.com users are 1% lower than those paid by other customers (see column 1 in Table 4). This estimate is smaller than the 1.5% we found in an earlier paper in which we had data only from California (Scott Morton, Zettelmeyer, and Silva-Risso 2001). Purchasing from an Autobytel.com affiliated dealer, regardless of what channel was used to buy the car, is associated with a price that is lower by about 0.5%, unchanged from our earlier estimates.

The second column of Table 4 adds demographics. Because an individual buyer is assigned the demographic characteristics of her census block group, the explanatory variables are either a probability that a characteristic applies to the customer (such as *%CollegeGraduates*) or an average/median (such as *MedianHHIncome*). The two exceptions to this are *Age*, which is the actual age of the customer, *Over64*, which is a dummy indicating if the person's age is above 64, and *Female*, which is inferred by MRI based on an analysis of the buyer's first name. We use all the census demographics to predict price as well as two interactions. The first is *Female* interacted with *Over64*, while the second is *%Black* interacted with (500 - *MedianHouseValue*).[13]

The Autobytel.com results in column two are very similar to those in column one. The Autobytel.com coefficient falls slightly in magnitude to -.89%. Again, buyers who purchase at an Autobytel.com franchise pay lower prices. The demographic coefficients have the expected signs. In particular, older people pay more for cars (0.2% increase if age moves from 20 to 64) until a consumer hits retirement age, whereupon a negative indicator variable of -0.16% takes effect. People who have a higher probability of being a disadvantaged minority (black and Hispanic) pay more. An increase from zero to one hundred percent Hispanic in a census tract raises the expected price of the car by 1.1%. The same increase in percent black in a neighborhood with housing prices one standard deviation below the mean results in a 1.2%

[12] Many of the attributes of the car, such as being sold in Northern California or in December, are more appropriately modeled as a percentage of the car's value instead of a fixed dollar increment.

[13] *MedianHouseValue* refers to the median house value in a census block group and is measured in $1000. 500 is the maximum *MedianHouseValue* over all census block groups.

increase in transaction price on average. For more details on the effect of race on car prices, see Scott Morton, Zettelmeyer, and Silva-Risso (2003). Women pay about 0.2% more than do men for a given car. We expect income and education to be correlated, and we also expect them to have opposite effects on car prices. High income indicates a lower elasticity of demand, while high educational levels may make a person a more effective bargainer. Hence, we have few priors on the signs of these neighborhood variables. They are mostly significant: more income and high house values are associated with lower car prices, while consumers in a more "professional" neighborhood pay higher prices. Home ownership, a proxy for good credit, is associated with lower prices. Buyers from neighborhoods with a higher proportion of *%CollegeGraduates* pay lower prices, as we expected, while an increase of ten percent in the probability of not finishing high school in a census tract is associated with an increase in a resident's price by 0.03% on average.

4.2 Results by vehicle segment

We find that there is considerable variation in the Autobytel.com discount by vehicle subsegment (see Table 5). MRI separates the cars in the dataset into sixteen subsegments such as "compact pickup" and "premium sporty." Four subsegments—Basic Large, Luxury SUV, Near Luxury, and Premium Sporty—have Autobytel.com coefficients that are smaller than one-half percent (the Traditional Luxury subsegment has an insignificant coefficient, though it is larger that 0.5 in magnitude.) Consumers may have received little or no Autobytel.com discount because there was strong demand for the cars in these subsegments in 1999. We check for the strength of demand in a subsegment by comparing average *DaysToTurn* across subsegments. This variable measures how long a car sits on a dealer's lot and therefore how popular it is. The subsegments with the fastest turnover (lowest median days to turn) are: International Luxury (11), Luxury SUV (10), Near Luxury (14), and Premium Sporty (10). (For comparison, the median subsegment in terms of median days to turn, Premium Compact, has a median number of days to turn of 25.) This list includes three out of the four subsegments with the lowest Autobytel.com discounts. The Basic Large subsegment does not have excess demand by this metric, but the segment is very small and dominated by institutional purchases (Police Departments), and is therefore atypical. Consumers who buy cars in the "entry" and "compact" subsegments such as "Compact Pickup," "Entry Sporty," "Premium Compact," and "Entry Compact" receive the largest Autobytel.com discount. It appears that the Autobytel.com coefficient is largest for car categories that are not supply constrained.

4.3 Competitive Effects

Prices are higher when dealers are in areas with fewer other dealers of the same nameplate (see column 1 in Table 6). Moving from zero to ten other dealers of the same nameplate within ten miles lowers the average price by approximately 0.3% ($69 on the average car). This effect may be small because our data do not include sales in rural areas, so we do not have as much variation in market structure as do some other studies.

We are also curious as to whether Autobytel.com creates an effect similar to adding another competitor to the marketplace. For example, in a concentrated local market, the availability of getting a price quote over the web might be equivalent to increasing competition in the local market. If so, we would expect the price discount obtained by using Autobytel.com to be higher in less competitive markets. As the market becomes more competitive, the addition of another competitor should have less effect on equilibrium prices (Bresnahan and Reiss 1991).

The institutional role of Autobytel.com suggests that Autobytel.com could also have the opposite effect. Bargaining over price may effectively occur between the dealer and Autobytel.com, in addition to between the customer and the dealer. In such a case, more dealers in an area will strengthen the hand of Autobytel.com because it can credibly threaten to move its franchise to another dealer more easily. A greater density of dealers may allow Autobytel.com to more easily pressure dealers into offering lower prices to consumers. We find that the interaction between Autobytel.com and the number of dealers of the same nameplate in the area is negative (see column 2 in Table 6). It appears that Autobytel.com has more influence on dealer pricing in more competitive markets, and that this effect is larger in magnitude than that of the simple competition measure.

4.4 Discussion

The results show that dealerships that contract with an Internet referral service set lower offline prices than do other dealerships, and that consumers who submit a purchase request pay a lower price than do other consumers at that dealership. Any potential convenience and income effect is dominated by price-reducing effects. Online consumers who buy through Autobytel.com pay on average 1% less than do offline consumers, for the same car. On average, consumers who shop at an Autobytel.com contract dealer gain slightly relative to shopping at a non-Autobytel.com contract dealer. The payoff from using Autobytel.com increases as the local market becomes more competitive.

To test for whether the volume-based compensation that Autobytel.com encourages for Internet salespeople may be contributing to lower prices, we limit the sample to cars purchased on the last two days of the month. The volume incentives facing dealers on those days are similar to the volume incentives Autobytel.com suggests dealers use for salespeople handling its leads. Thus the two groups should be more similar at this time of the month if part of what is driving the Autobytel.com "discount" is salesperson behavior. We find only a small drop in the Autobytel.com coefficient to about -.78% in this specification (see column 3 in Table 4). Since much of the previously estimated Autobytel.com discount remains when estimated on a sample of cars which are all sold under volume-based incentives, this suggests that volume-based compensation plays only a small role in the lower prices paid by Autobytel.com consumers.

5 Selection

Thus far we have not attempted to discriminate between two different interpretations of the finding that Autobytel.com customers pay less: (1) the referral service attracts consumers who subsequently pay lower prices than they would have if Autobytel.com had not been available, or (2) the referral service attracts consumers who would have paid the same prices in the absence of the Internet because they would have used other means to obtain a low price. Formally, consider the following set of equations where C is an individual specific characteristic that is unobserved and forms part of the error term.

$$
\begin{aligned}
Autobytel_i &= \gamma Z_i + \alpha C_i + \mu_i = \gamma Z_i + \epsilon_{1\,i} \qquad (1)\\
\ln\left(Price_i\right) &= \phi Autobytel_i + \beta X_i + \delta C_i + \nu_i = \phi Autobytel_i + \beta X_i + \epsilon_{2\,i} \qquad (2)
\end{aligned}
$$

Suppose C is the ability to gather information and use it in the bargaining process. This characteristic ("cowboy") causes the buyer to use Autobytel.com to strengthen her bargaining position, leading to positive α and a negative δ. Since C is unobserved, *Autobytel* will be correlated with equation 2's error term. In this scenario the estimated coefficient on *Autobytel* will be negatively biased relative to the true coefficient.

The selection effect could also work in the opposite direction. Suppose that characteristic C indicated that the buyer has high personal cost to collecting information and bargaining ("coward"). Then α would be positive, but δ would be positive also. Hence, the estimated Autobytel.com coefficient will be biased upward and the true savings from using the service will be larger than the OLS estimates. This latter direction of the selection effect is consistent with new car buyers behaving rather like standard adopters of a new technology over time.[14] The agents – consumers in our case – who are first to adopt the new technology, an Internet referral service, have the most to gain because they would pay a high price in the traditional

[14]This literature is traditionally focused on firms, for example, farming (Griliches 1957) and steel (Oster 1982).

channel.

5.1 Instrumental Variables Estimation

In order to estimate the true effect of Autobytel.com usage on price, we use an instrumental variables procedure. The unobserved characteristic that could potentially determine both Autobytel.com usage and negotiated prices is an individual's ability or desire to price negotiate, for example by gathering information and using it in the bargaining process. Our instruments must therefore predict usage of Autobytel.com but be uncorrelated with this characteristic. In other research settings demographic information can be used to predict Internet usage. In the case of negotiated prices, however, almost all demographic indicators (for example, income or education) are likely also to be correlated with price, making it particularly difficult to find good instruments.

Instruments for *Autobytel*: We introduce a series of instruments for *Autobytel*. For each instrument we detail (1) why we think that this instrument is correlated with Autobytel.com usage and (2) why we think that this instrument is uncorrelated with an individual consumer's ability or desire to bargain.

Our first instrument is the number of franchises which have a contract with Autobytel.com and are in close proximity to the consumer. Specifically we count the number of Autobytel.com contract franchises which are in a zip code whose centroid is within 5 miles of the centroid of the zip code the consumer resides in. This instrument is likely to be correlated with whether consumers use Autobytel.com due to worth of mouth. We expect that more neighboring consumers will have successfully used Autobytel.com referrals if more Autobytel.com contract dealers are close by. This is because such customers are more likely to have have purchased from an Autobytel.com contract dealer after a referral, or have been able to use a competitive offer from a close Autobytel.com contract dealer to negotiate with a non-affiliated dealer. We also expect that this instrument proxies for whether consumers use Autobytel.com due to local Autobytel.com advertising that drives consumers online (which, unlike national advertising, we cannot measure). The number of close Autobytel.com contract franchises is unlikely to be correlated with consumer's ability to bargain. Our conversation with Autobytel.com managers did not indicate that during 1996-1999 the company took regional variations in consumers' ability to bargain into account when signing up dealers.

Our second set of instruments is based on the regional price variation of the car the consumer is purchasing. Specifically, we include two coefficients of variation for the price of the car the consumer buys. We construct these instruments as follows: First we run our standard hedonic price regression on all non-Autobytel observations. For each geographic region we then calculate the standard deviation of the estimated residual from this regression for all transactions of a specific car. We also calculate the mean price for the same car in each region. To construct the instrument we divide the standard deviation of the residuals for each car for each region by the mean price of the corresponding car for the corresponding region. We calculate this coefficient of variation at the level of the car definition used in the regression fixed effects (*PriceVariation1*). We also calculate it for the next level of aggregation by combining engine sizes of the same car (*PriceVariation2*). Whether or not consumers decide to request a referral from Autobytel.com is likely to be driven by the price offers they receive from dealers as they begin searching for a car and therefore correlated with our price variation measures. Whether higher or lower price variation is correlated with using Autobytel depends on the decision process consumers follow. For example, consumers who have not been able to find a comparatively low price after several enquiries at dealers may decide that visiting additional dealers is not going to yield a low price offer and thus try a online referral as an alternative way to obtain a low price. In this case we would expect that lower price variation is associated with a higher probability of using Autobytel.com. Alternatively, consumers who receive strongly varying price offers from dealers during their initial search may interpret this as evidence that a referral from Autobytel.com will be particularly beneficial. In this case we would expect that higher price variation is associated with a higher probability of using Autobytel.com. These measures will be uncorrelated with an individual consumer‘s ability to bargain because, even if consumers with a higher ability to bargain systematically buy particular cars, the common price effect would be absorbed by the car fixed effects in the price equation.

Our third instrument is the number of transactions in the sample for a particular "car" (*#ofCarsSold*). The popularity of certain bundles of characteristics should affect the benefit to searching for the car on the Internet and therefore the likelihood of doing so. How the popularity of certain bundles of characteristics will be correlated with a higher probability to use Autobytel depends on the decision process consumers follow. For example, consumers who believe that dealers use Autobytel.com to sell cars without haggling and at low prices might expect that the more common car configurations are more likely to be sold under this model, while rare configurations are sold with negotiation to consumers who are specifically looking for them. Alternatively, consumers may assume that more popular cars are easier to search for at multiple dealers, leading to fewer opportunities to find a lower price using Autobytel.com. Note that we eliminated extremely rare cars from the sample; *#ofCarsSold* is always 300 or larger. *#ofCarsSold* will be uncorrelated with a consumer's ability to bargain because the measure is constant across consumers within a car type. Hence, even if consumers with a higher ability to bargain systematically chose more or less popular cars, the price effect would be absorbed by the car fixed effects in the price equation. Since *#ofCarsSold* is constant within a car type, one might think that the car fixed effects in the price regression would cause this instrument to be unable to identify the effect of Autobytel across consumers within a car. However, the marginal impact of *#ofCarsSold* is constant only within the probit index. Because of the nonlinearity of the probit index, the marginal effect of the measure on the probability of using Autobytel.com are will differ across consumers because they differ in other characteristics in the index. Thus the effect of *#ofCarsSold* on the probability of using Autobytel will be higher for some demographic combinations. However, these demographic combinations are not a source of unobserved price variation; all demographics are included in the price regression. There is no reason we can think of that would cause *#ofCarsSold* to be correlated with the non-demographic, unobservable ability to bargain which is a component of price.

Our fourth instrument is a measure of Autobytel's national television advertising spending.[15] This instrument varies by week but not by location. This instrument will be correlated with Autobytel.com usage if the advertising is likely to inform consumers about the existence of Autobytel and persuades some to request a referral. Thus, the instrument should predict Autobytel.com usage over time. It seems reasonable to assume that this instrument is uncorrelated with price and an individual's ability to bargain: given the relatively small size of Autobytel.com in 1999, we do not expect dealers to condition their prices on Autobytel's advertising schedule. Ideally we would like to match the date of advertising spending to the date of a given referral. However, since we do not observe a consumer's decision *not* to obtain a referral, such matching is not possible, and so we must rely on the purchase date of a vehicle instead. The measure that best predicts referrals is the sum of advertising spending two and three weeks before the vehicle purchase, and this is what we use as an instrument.[16]

Lastly, we interact some of the above instruments with demographic measures and competition. For example, there is evidence that men are more likely to watch the sports and late-night TV that comprised much of the Autobytel.com advertising spending. So we create an additional instrument which is the advertising measure interacted with the buyer's gender (1-*Female*). We also conjecture that educated consumers will know better when obtaining an Autobytel referral is more valuable as a function of a car's price variation. So we interact the coefficient of variation for a car with *%CollegeGraduates*. Lastly, we interact our measure of how common car configurations are (*#ofCarsSold*) with the level of dealer competition in the surrounding area. The rationale for this interaction is that the savings in search costs of using

[15]Due to confidentiality concerns, the unit of measurement was not given to us but remains constant across all 58 weeks (1999-Feb 2000) (Mean=2.58; Std.Dev.=2.38; Min.=0; Max.=7.5)

[16]If a consumer purchased a car on Monday through Wednesday we use as instrument for Autobytel.com usage the sum of the firm's advertising expenditure two and three weeks prior to the purchase date. If a consumer purchased a car on Thursday through Sunday we use as the instrument the sum of the Autobytel.com's advertising expenditure one and two weeks prior to the purchase date.

Autobytel for more common car configurations should decline if there are many local dealers.

We experimented with instruments from the Current Population Survey Internet and Computer Use Supplement. For example, owning a computer and having high speed Internet access in one's geographic area clearly lower the cost of using Autobytel.com, and not surprisingly, help predict who uses the service. However, they also predict the price a consumer pays for her car, so we could not use them as instruments. (Formal overidentification tests of our instruments are reported below.)

Instruments for *AutobytelFranchise*: We also require an instrument for *AutobytelFranchise*. This is because consumers who have requested an Autobytel.com referral are more likely to end up purchasing from an Autobytel.com contract dealer than is the average offline consumer. Since Autobytel.com franchise usage is correlated with Autobytel.com usage, and *Autobytel* is correlated with the error term in the price equation, so is *AutobytelFranchise*. We would like an instrument that is correlated with the propensity of an individual to purchase a car at an Autobytel.com contract dealer but is uncorrelated with the individual's ability or desire to bargain. For our instrument, we calculate how much closer the consumer lives to the closest dealer of the make he or she purchased than to the nearest Autobytel.com affiliated dealer of the same make. This variable is correlated with whether a consumer purchases at an Autobytel.com contract dealer because it measures the additional distance a consumer needs to travel to get to the closest Autobytel.com dealer of the relevant make. We also include a measure of the absolute distance to the closest dealer of the relevant make. It seems unlikely that consumers' ability or desire to bargain determines their relative distance to an Autobytel.com franchise or to car dealers in general.

Estimation: Our estimation procedure follows that of Wooldridge (*Econometric Analysis of Cross Section and Panel Data*, 2002, page 623) for the case of dichotomous endogenous variables.[17] In particular, we estimate the determinants of Internet use using a probit regression of *Autobytel* on our instruments and all exogenous variables in the price regression. We also estimate a second probit regression of *AutobytelFranchise* on our instruments and all exogenous variables in the price regression. We use both predicted probabilities as the instruments for *Autobytel* and *AutobytelFranchise* in the price regression.[18] Wooldridge (2002) details the properties of the estimator and notes that two of its virtues are that the usual IV standard

[17] Other papers proposing estimation strategies for similar problems include Angrist (2001) and Heckman (1978).

[18] One can also include the original instruments linearly in addition to the predicted probability and obtain almost identical results.

errors are correct, and that the estimator is robust to mis-specification of the probit model. We report the estimates from the probit regressions in Table 7.

In the *Autobytel* equation we find, as predicted, that the number of Autobytel.com franchises in the local area is positively related to whether consumers request a referral from Autobytel.com. Variation in the price (*PriceVariation1*) of the focal car is positively related to Autobytel.com usage while variation in price in the next most aggregated car (*PriceVariation2*) has a negative effect on Autobytel.com usage. The cumulative effect is negative in price variation, consistent with consumers who have not been able to find a comparatively low price after several enquiries at dealers deciding that visiting additional dealers is not going to yield a low price offer and thus trying an online referral as an alternative way to obtain a low price. The effect is the opposite for college educated buyers *PriceVariation2*%CollegeGraduates*; these buyers may be aware of the price distribution for their car of interest before searching, and use Autobytel when the returns are greatest. We find that consumers are more likely to request an Autobytel.com referral for more common car configurations. This is consistent with consumers believing that the most common car configurations are the ones that are most likely to be sold under a model in which dealers use Autobytel.com to sell cars without haggling and at low prices. This effect is attenuated when there are many dealers in the local area. Finally, the advertising measures are not significant. This could be because there is large heterogeneity in the length of time between a referral and the car purchase; 25% of consumers buy a car within 7 days of their referral, half within 22 days, and 75% within 72 days. Since we have to match the week of advertising spending to the purchase date and not the referral date, any given lag with which we construct the advertising instrument will predict referrals poorly for some consumers. Other variables enter the first stage in expected ways. For example, young people, better educated people, and those in neighborhoods with a high share of technical workers are more likely to use Autobytel. Men, especially young men, are more likely to use Autobytel, while minorities, especially those in neighborhoods with low housing values, are less likely to use Autobytel. The pseudo R-squared is 0.06, indicating that there is substantial unexplained variation in Internet use.

The regression of *AutobytelFranchise* is similar, with the exception that the instruments explain more of the variation (pseudo R-squared is 0.1). The incremental distance between the Autobytel.com dealer and the closest non-Autobytel.com dealer is highly significant (and negative, as expected) in explaining *AutobytelFranchise* use. A one standard deviation increase in relative distance changes the probability that a consumers buys at an Autobytel franchise dealer by -0.18. The closer the closest dealer of the relevant nameplate is to the consumer's address, the lower the probability that the consumers will purchase at an Autobytel franchise dealer (which is further away on average).

IV results and robustness: The results from the 2SLS specification follow in Table 8. The estimated coefficient on *AutobytelFranchise* is -2.41% while the coefficient on *AutobytelFranchise* increases in magnitude to -1.01%. Both estimates are significantly different from zero at a 1% significance level. In this and all subsequent specifications the instruments pass a test of overidentifying restrictions described in Hausman (1983). The test statistic is $N * R^2$ from a regression of the IV errors on all the exogenous variables in the system. It is distributed χ^2 with K-1 degrees of freedom, where K is the number of instruments.

We include in the remainder of Table 8 the estimated Autobytel coefficient with one instrument and its interactions excluded in each estimation. The Autobytel coefficient is robust to most combinations and varies between -2.13 and -2.69; the exception to this is the case where the advertising variable and its interactions are excluded. Then the coefficient increases to -2.96. The *AutobytelFranchise* coefficient is very precisely estimated (t-stats of approximately 18) because distance is such a good instrument for this variable. It varies very little across combinations of Autobytel instruments.

5.2 Discussion

A consumer buying through Autobytel.com is estimated to save 2.4%, corresponding to over $500 on the average car. This is larger in magnitude than the OLS point estimate. We conclude that the negative sign of the OLS coefficient is not an artifact of selection of savvy consumers into use of the Internet. Rather, it appears that the lower prices associated with Autobytel.com usage are caused by Internet use. This implies a change in the overall distribution of prices. Below we plot the distributions of prices in the two channels to see how they are affected.

Figure 1 on page 43 plots the distribution of residuals from our basic price regression (column 2 in Table 4 excluding Autobytel.com related explanatory variables). Residuals from Autobytel.com sales are plotted below those of non-Autobytel.com sales. The distribution of residuals for Autobytel.com sales is of lower mean and variance than those of "street" sales. Notice also that the Autobytel.com distribution has a much thinner upper tail than the non-Autobytel.com distribution. The lower tails of the two distributions are very similar. This is what we would expect to see if consumers who would have paid an above average price pay a price closer to the mean after using the Internet.

Notice also that the difference between the OLS and the IV estimates indicates that consumers who use Autobytel.com would have paid above average prices offline. Taking the coefficients at face value, the OLS estimates indicate that consumers who use Autobytel.com pay approximately .9% below the average for the rest of the sample for a given car. The IV estimates, which correct for selection and, under the identifying assumptions, consistently estimate the true treatment effect, estimate the effect of Autobytel.com usage on price at approximately 2.4%. In order to reconcile a treatment effect of 2.4% with an average effect of 0.9%, it must be that Autobytel.com consumers should have paid about 1.5% *above* the average in the rest of the sample, had they not used Autobytel.com. While this difference suggests that it is the "cowards" who are disproportionately likely to use Autobytel.com, the statistical precision of our results does not allow us to conclude this definitively. In particular, the OLS estimate of *Autobytel* would be excluded only by the 91% (not the 95%) confidence interval of the IV estimate (from a Wald test of the hypothesis that the IV estimate is equal to 0.9%). Since we would like more evidence on this critical point, we now turn to direct measures of customer types and Internet usage.

5.3 Evidence from survey data

We want to determine whether consumers who consider themselves disadvantaged in the traditional face-to-face bargaining process are more likely to use the Internet. Since our large dataset of transactions lacks information which would allow us to directly measure a consumer's cost of bargaining or collecting information, we have gathered a second set of data which contains such measures. These data also contain information on whether consumers used the Internet to shop for a car. We can therefore relate consumer types to their likelihood of using the Internet.

Data: We mailed a survey instrument to 5250 consumers who purchased one of eight popular new car models in California during April and May 2002. The survey asked questions about buyers' search and bargaining behavior as well as their personal attitudes towards bargaining and information search (see Zettelmeyer, Scott Morton, and Silva-Risso (2006) for more details and a list of questions used in this paper).

We chose our sample by car type and then mailed the survey to every consumer of the selected car types who had purchased a car in April and May 2002 at a sample of dealers. The objective in selecting car types was to include a variety of car categories (e.g. midsize sedan, luxury sedan, pickup, SUV, etc.). This is because we knew from earlier results that Internet search could affect different car categories differently. We added the purchases of the most common cars for a variety of car categories until we reached our desired sample size. This yielded the most popular variants of the following cars: Honda Accord, Chrysler PT Cruiser, Nissan Altima, Chevrolet Silverado, Toyota Corolla, Jeep Grand Cherokee, Honda Odyssey, and Chevrolet Tahoe.

Each potential respondent received three mailings. The first mailing contained a letter announcing the arrival of the survey, introducing ourselves as the researchers and explaining the purpose of the project. The second mailing was sent out 5 days later and contained a cover letter, the survey, a pre-stamped return envelope, and a $1 bill. The third mailing was sent out 5 days after the second mailing and consisted of a postcard thanking buyers for their participation and reminding them to return the survey. We achieved a response rate of 47%.

Which consumers types are more likely to use the Internet? In our survey we asked consumers to rate their agreement or disagreement with a list of statements to get a measure of three consumer traits that we thought, ex ante, could be the unobserved characteristic in our model. These traits are (1) whether a consumer has a high disutility of bargaining, (2) whether a consumer has a high willingness to search, and (3) whether a consumer is a knowledgeable about cars. To get answers that are reliable and as comparable as possible across respondents, we ask survey participants questions about their behavior or attitudes, not about the traits directly. For example, we are interested in the "car knowledge" trait to control for whether a consumer knows a lot about cars, even if they did little or no search for their car purchase. We asked questions like "I read car- and/or truck-enthusiast magazines regularly" and "I tend to visit dealers whenever a new model is introduced." Similarly, we get at consumers' willingness to search with statements such as "I do a lot of price comparison when making large purchases," and "I am the kind of person who gathers as much information as possible before visiting car dealers." Finally, to assess whether a consumer has a high disutility of bargaining, we present consumers with statements such as "I am the kind of person who enjoys negotiating the car's price with the dealer," and "I am afraid that I will be taken advantage of by a dealer when negotiating the price of a new car." We also assess consumers' available time to engage in the bargaining process with the statement "It is hard for me to find time to shop for a new vehicle."

We assess how well the three consumer traits predict Internet usage by including the answers to the statements directly in probit specifications of *InternetUse* and use of Internet referral services such as Autobytel.com (*IRSUse*). These specifications also control for demographics on a census block group level. Gender is inferred from an analysis of first names. Table 1 on page 32 presents summary statistics for the survey data.[19]

We find support that consumers with a high disutility of bargaining are more likely to go online (see columns 1 and 2 in Table 10). Respondents who *disagree* with "I am the kind of person who enjoys negotiating the car's price with the dealer" are more likely to use the Internet and visit the websites of Internet referral services. In addition, we find that respondents who agree with "I am afraid that I will be taken advantage of by a dealer when negotiating the price of a new car" are more likely to use Internet referral services. We also find that consumers with a lack of time are more likely to use an Internet referral service. Consumers' response to

[19]The 1752 observations used in the probit are somewhat smaller than the number of returned surveys because of missing data.

“It is hard for me to find time to shop for a new vehicle” is positively related to *IRSUse*.

Not surprisingly, consumers with a high willingness to search are also more likely to go online. Consumers who agree with “I am the kind of person who gathers as much information as possible before visiting car dealers,” and with “I am the kind of person who tries to find out the dealer’s invoice price on a car before going to the dealership to shop” are more likely to use the Internet as well as to use Internet referral services. We find that people knowledgeable about cars are less likely to use the Internet.

Conclusion from the survey The survey findings are consistent with our conjecture from the IV results, namely that “cowards” are disproportionately likely to use Autobytel.com: We find in the survey that consumers with a high disutility of bargaining are more likely to go online. Under the reasonable assumption that such consumers pay higher prices than consumers who enjoy the bargaining process, this finding would be consistent with the observed difference between our OLS and IV results, namely that the IV coefficient on Autobytel.com usage is larger in magnitude than the OLS coefficient.

We also find that a high willingness to search is associated with higher online usage. Under the reasonable assumption that such consumers pay lower prices than consumers with a low willingness to search, the implied selection effect should lead to an OLS coefficient of a larger magnitude than the IV coefficient of Autobytel.com usage. However, we cannot find evidence in our results that this effect is empirical important.

We conclude that the survey shows evidence of consumer traits which could result in biasing the Autobytel.com coefficient either way when these traits are not controlled for. Our results from the transaction data suggest that the selection bias due to the fact that consumers with a higher disutility of bargaining are more likely to go online dominates the potential selection bias due to the fact that consumers with a low willingness to search are more likely to go online.

5.4 Invoice prices and selling cost

Our findings raise the question of whether the lower prices obtained by dealers for online consumers are offset by lower costs. If this is so, the Internet leads to lower prices without decreasing dealers’ unit profits. The first thing to compare is dealer vehicle margins. We have shown that Autobytel.com sales to occur at lower prices. If the invoice prices are lower also, then margins could be preserved. In a levels regression, we find that the vehicle costs of Autobytel.com affiliated dealerships are on average \$64 higher per car than at unaffiliated dealerships. In a log regression, costs are higher by 0.29%, or \$68 on the average car (see columns 1 and 2 in Table 11). Although invoice price appear to be higher for Autobytel.com affiliated dealerships, dealer franchise laws require manufacturers to sell the same car at the same price to all dealers in a region. The higher vehicle cost observed for Autobytel.com affiliated dealerships thus indicates that those dealerships sell cars with more expensive options which are not captured by our car dummies.[20] Since invoice prices are not lower for Autobytel.com dealers, any potential cost savings from selling to Autobytel.com customers must come out of dealers' overhead costs.

Autobytel.com may also reduce the selling costs of dealers by increasing the productivity of a salesperson. Since some of the customer communication is handled by e-mail, a sales person can potentially spend less time for each sale. Regrettably, we cannot test this hypothesis with our transaction data because we do not have information on overhead cost. However, we have no evidence that the lower margins can be fully offset by lower overhead cost.[21]

6 Car and dealer switching

Having shown that Internet referral services lower prices for retail auto sales, in this section we attempt to understand better what aspect of a referral enables consumers to obtain a lower price. We do so by exploiting differences in make, model, and dealer, between the Autobytel.com referral and the actual transaction.

6.1 Referral versus transaction dealers

We first analyze whether Autobytel.com usage leads to savings only at the dealer to whom the consumer was referred, or whether the referral is useful for negotiating with other dealers also. Consumers can take the price quote in response to a referral and the information obtained during the process, and try to negotiate a low price from a dealer not affiliated with the referral service.

We add to our basic specification an indicator identifying those Autobytel.com consumers who purchased the car from their referred dealer, *SameDealer* (see column 1 in Table 12). These consumers are "doing what they are supposed to" from the point of view of the dealer and the Autobytel.com business model. The coefficient on *SameDealer* is 0.19%, i.e. consumers who continue their (costly) search after having received a referral pay slightly less than consumers who do not continue searching. While this suggests that the information provided by Autoby-

[20] Because we control for *VehicleCost* in our price regressions, this has no effect on our previous results.

[21] In Scott Morton, Zettelmeyer, and Silva-Risso (2001) we were able to examine some anecdotal evidence which leads us to mixed conclusions about whether selling costs are lower for Internet sales. On the one hand we were able to examine accounting data provided to us by Autobytel.com for a dealer whom we suppose to be relatively cost efficient. This dealer claimed to have \$600 lower selling cost for Internet sales than for traditional sales. On the other hand, a survey (J.D. Power and Associates (2000a)) found that 51% of dealerships reported that it took them *more* man-hours to complete a sale with Internet customers from an Internet referral service than with traditional customers.

tel.com is portable, it also suggests that, on average, the benefit to consumers of continuing to search is small.

6.2 Referred versus purchased make and model

Next, we analyze whether consumer savings from using Autobytel.com are associated with the mere fact of submitting a referral, or whether it matters that consumers submit a referral for the specific make (nameplate) and model that they purchase. We can analyze this question because 51% of the consumers who use Autobytel.com do not purchase the car for which they made a purchase request.[22] Recall that up until this point in the paper, these buyers were excluded from the dataset.

We define these consumers as *ChangeCar* buyers rather than *SameCar* buyers. Of these *ChangeCar* buyers, 30% end up purchasing a car of the same make (but not model) as the car for which they made a purchase request. We previously noted that 28% of *SameCar* consumers buy from their referred dealer. For consumers who change make and model, only 6.75% buy from the referred dealer.

To compare a buyer's requested versus purchased model, we calculate the average price of each make and model in the dataset. We then compare the prices of the referred cars versus the purchased cars. We do this for the 79% of buyers who make exactly one referral request. We ignore the remaining observations because otherwise we would have to choose arbitrarily which request to analyze. We find that buyers who change cars, on average, request a price quote for a more expensive car than the one they buy. The median *ChangeCar* consumer buys a car that costs $500 less and that was on the lot for two more days than the requested car. Consumers seem to be searching for the lowest price on their "dream car" before resigning themselves to buying a less expensive alternative. Interestingly, we find that consumers who change models but not dealers, buy cars that are, on average more expensive than the ones they requested.[23].

We add a second Autobytel.com variable to our standard price specification. *Autobytel∗ChangeCar* is one if a consumer purchases a different make or model than the one requested through Autobytel.com. *Autobytel* continues to capture the effect of Autobytel.com for consumers who buy a make and model they requested. The sample size increases by 20,372 observations because we add consumers who purchased a different make or model from the one requested through Autobytel.com.

We find that the *Autobytel∗ChangeCar* coefficient is about half the size of the *Autobytel* coefficient, -0.46% versus -0.9% (see column 2 in Table 12). We can further distinguish between

[22] Our statistic includes consumers who submit multiple referral requests; if any of the requests matches the car bought, then the consumer is defined as *SameCar*.

[23] This may be a version of the "bait and switch" technique found in Ellison and Ellison (2004)

consumers who change make and model and those who only change model but purchase a car of the requested nameplate. We find that consumer who change make and model receive a -0.36% discount, those who stay with the same make get -0.7% and those who buy the car they asked about receive a -0.9% discount (see column 3 in Table 12). Finally, among *ChangeCar* consumers, there is no difference between the price paid by those who purchase from the referred dealer and those who switch dealership (see column 4 in Table 12).[24]

The fact that consumers get a bigger price reduction when they have information that is more relevant to the car they actually purchase suggests that consumers' bargaining outcomes are materially improved by the information they obtain on Autobytel.com. If instead Autobytel.com usage were simply a proxy for whether a consumer is a savvy bargainer, the "savvy bargaining" effect on the price would presumably not vary with whether the consumer ended up buying the car for which they originally requested a referral. Our finding that Autobytel.com usage is not a proxy for good bargaining ability is consistent with our IV results and the results of the survey.

Finally, this also provides evidence that the Autobytel.com discount is unlikely to be explained by lower selling costs. If the discount simply reflected lower cost, the effect on the price would presumably not vary with whether the consumer ended up buying the car for which they originally requested a referral.

7 Conclusion

This paper is concerned with whether the Internet can lower profits for an established offline industry. In particular, this paper has begun where Scott Morton, Zettelmeyer, and Silva-Risso (2001) left off by estimating the 'treatment effect' of an Internet referral service, Autobytel.com, on prices for retail auto sales. Using an instrumental variables approach to control for selection, we find that buying a car through Autobytel.com reduces the price a consumer pays by approximately 2.4%. This is in contrast to the on average 1% lower prices that online buyers pay compared to offline consumers, for the same car. This suggests that consumers who use an Internet referral service are *not* those who would have obtained a low price even in the absence of the Internet. Instead, our findings are consistent with consumers choosing to use Autobytel.com because they know that they would do poorly in the traditional channel. We find support for this conjecture by analyzing survey data that directly measures consumer traits and Internet use. We find that consumers who expressed a high disutility of bargaining and lack of time were more likely to go online. In the terminology used to distinguish be-

[24]Recall that for *SameCar* consumers, buying from the referral dealer is slightly more expensive (and more convenient) than continuing to price shop (by 0.19%).

tween the two selection stories, it seems that it is the "cowards," not the "cowboys" who are disproportionately likely to use the Internet.

As suggested by our selection results, we find that a dealership's Autobytel.com sales are associated with a reduction in high margin sales. We also find that having a make- and model-specific price quote lowers the price a customer pays by more than obtaining general information from the Internet, or having characteristics associated with Internet usage. This finding is also consistent with our selection result, namely that differences in the characteristics of Internet and non-Internet users cannot explain the lower prices paid by Autobytel.com consumers.

We cannot conclude definitively whether the advent of auto Internet referral services benefited Internet consumers. This is because we do not know whether average offline car prices increased or decreased in reaction to the introduction of these services. If offline prices increased on average, dealers could offer discounts to Internet users without making these consumers better off than they would have been in the absence of the Internet. However, the number of buyers who used Internet referral services was small in 1999. Thus, it may not be unreasonable to assume that overall price levels had not changed as a result of the Internet in 1999. Under this assumption the consumers in our sample saved \$10 million in aggregate. If we extrapolate the results here from the 3% of the sample that uses Autobytel.com and buys the car they requested to the portion of the market not covered by the MRI data, the aggregate savings to Internet consumers could have been about \$240 million per year. We do not think that this result reflects a steady state in the US auto industry, since the Internet was relatively new at the time of our data, and dealers and consumers seem unlikely to have fully adjusted to the existence of online referral services. However, our results suggest that in our sample period Autobytel.com, and perhaps other referral services, were facilitating a substantial redistribution of surplus in the retail auto industry.

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Appendix

Survey questions for Section 5.3

Internet usage measures:

InternetUse: “Did you use the Internet in any way to help you shop for a new vehicle? (e.g. to research vehicles, find a dealer, etc.)” Answer categories: yes/no

IRSUse: “For each source of information on the Internet you used to shop for a new car, please tell us how it was used:”
Answer categories: “To determine ... which car to purchase, which dealers to visit or buy from, manufacturer suggested retail price, the dealer cost (invoice/hold- back), fair price or market value for the car.” The indicator *IRSUse* is “1” (“0” otherwise) if the respondent checks any of the response categories for the source of information “Online buying services (e.g. Autobytel.com, Carpoint.com, Autoweb.com, Cars.com, Carsdirect.com, CarClub.com, Sam’s or Costco’s Internet Referral service, Driversseat.com, AutoVantage.com, Vehix.com)”

Consumer trait measures:
“Please tell us how you feel about the following statements:”
Answer categories: disagree strongly/disagree/agree/agree strongly

LikeNegotiating: “I am the kind of person who enjoys negotiating the car’s price with the dealer”
AfraidTakenAdvantage: “I am afraid that I will be taken advantage of by a dealer when negotiating the price of a new car”
NoTimeToShop: “It is hard for me to find time to shop for a new vehicle”
DoPriceComparisons: “I do a lot of price comparison when making larger purchases”
GatherMuchInfo: “I am the kind of person who gathers as much information as possible before visiting car dealers”
TriesFindInvoice: “I am the kind of person who tries to find out the dealer?s invoice price on a car before going to the dealership to shop”
ReadCarMagazine: “I read car- and/or truck- enthusiast magazines regularly”
VisitDealerForFun: “I tend to visit dealers whenever a new model is introduced”

Table 1: Summary statistics

Variable	Mean	Std.Dev.	Min	Max	Obs
Autobytel	0.03	0.17	0	1	663125
ABTFranchise	0.24	0.43	0	1	663125
SameDealer	0.01	0.09	0	1	663125
Price	23373.89	8091.31	6014	100190	663125
TradeInOverAllowance	954.64	1731.74	-10000	19956	266313
VehicleProfit	1437.29	1297.95	-4894	13902	663125
HadTradedIn	0.4	0.49	0	1	663125
AnyFinancing	0.75	0.43	0	1	663125
Trade	0.4	0.49	0	1	663125
Income	56.64	24.89	10.4	150	663125
Income^2	3827.3	3562.7	108.22	22500	663125
%HouseOwnership	0.73	0.22	0	1	663125
MedianHouseValue	164.88	99.66	7.5	500	663125
%CollegeGrad	0.31	0.18	0	1	663125
%LessHighSchool	0.12	0.11	0	1	663125
%Professional	0.16	0.08	0	1	663125
%Executives	0.17	0.08	0	1	663125
%BlueCollar	0.26	0.15	0	1	663125
%Technicians	0.03	0.02	0	1	663125
CustomerAge	43.9	14.12	16	100	663125
Age> 64	0.09	0.29	0	1	663125
Female	0.36	0.48	0	1	663125
Female*Over64	0.03	0.17	0	1	663125
%Hispanic	0.08	0.1	0	0.55	663125
%Black	0.06	0.14	0	1	663125
%Black*MedianHouseVal.	22.77	60.58	0	492.5	663125
%Asian	0.05	0.08	0	1	663125
EndOfMonth	0.22	0.42	0	1	663125
Weekend	0.23	0.42	0	1	663125
VehicleCost	0	0.06	-0.64	0.73	663125
Model Age 5-13 Months	0.73	0.44	0	1	663125
Model Age > 14 Months	0.11	0.32	0	1	663125
#ofCarsSold	2704.96	2265.37	300	12063	663125
#ofCarsSold*Competition	8417.87	11190.21	0	120960	663125
# of ABTFranchises w/in 5 m.	6.12	6.95	0	71	663125
PriceVariation1	0.04	0.01	0	0.24	663125
PriceVariation2	0.04	0.01	0	0.24	663125
PriceVariation2*%College	0.01	0.01	0	0.14	663125
ABTAdvertising	2.37	2.37	0	7.5	663125
ABTAdvertising*Male	1.51	2.21	0	7.5	663125
ABTFranchiseExtraDistance	12.1	23.87	0	2483.46	663125
DealerDistance	5.14	7.71	0	1064.76	663125

Table 2: Summary statistics by *Autobytel*

Variable	Autobytel=0 Mean	SD	Min	Max	Obs	Autobytel=1 Mean	SD	Min	Max	Obs
ABTFranchise	0.23	0.42	0	1	642753	0.39	0.49	0	1	20372
SameDealer	0	0	0	0	642753	0.28	0.45	0	1	20372
Price	23340	8113	6014	100190	642753	24440	7306	6995	89900	20372
TradeInOverAll.	965	1739	-10000	19956	260317	483.8	1324	-6250	17590	5996
VehicleProfit	1439	1300	-4894	13902	642753	1377	1232	-2559	11801	20372
Trade	0.41	0.49	0	1	642753	0.29	0.46	0	1	20372
AnyFinancing	0.75	0.43	0	1	642753	0.63	0.48	0	1	20372
HadTradedIn	0.41	0.49	0	1	642753	0.29	0.46	0	1	20372
Income	56.35	24.8	10.4	150	642753	65.63	25.87	10.68	150	20372
Income^2	3791	3541	108.22	22500	642753	4977	4018	113.96	22500	20372
%HouseOwners.	0.73	0.22	0	1	642753	0.74	0.23	0	1	20372
MedianHouseVal.	163.7	99.1	7.5	500	642753	201.1	110.1	7.5	500	20372
%CollegeGrad	0.31	0.18	0	1	642753	0.38	0.18	0	1	20372
%LessHighSchool	0.13	0.11	0	1	642753	0.09	0.08	0	0.75	20372
%Professional	0.16	0.08	0	1	642753	0.19	0.09	0	1	20372
%Executives	0.17	0.08	0	1	642753	0.2	0.08	0	1	20372
%BlueCollar	0.26	0.15	0	1	642753	0.21	0.13	0	1	20372
%Technicians	0.03	0.02	0	1	642753	0.03	0.02	0	0.28	20372
CustomerAge	43.98	14.17	16	100	642753	41.32	11.99	16	96	20372
Age> 64	0.09	0.29	0	1	642753	0.04	0.2	0	1	20372
Female	0.36	0.48	0	1	642753	0.33	0.47	0	1	20372
Female*Over64	0.03	0.17	0	1	642753	0.01	0.11	0	1	20372
%Hispanic	0.08	0.1	0	0.55	642753	0.07	0.08	0	0.54	20372
%Black	0.06	0.15	0	1	642753	0.04	0.1	0	1	20372
%Black*HouseVal.	23.03	61.12	0	492.5	642753	14.59	38.9	0	480.27	20372
%Asian	0.05	0.08	0	1	642753	0.06	0.09	0	0.97	20372
EndOfMonth	0.22	0.42	0	1	642753	0.24	0.43	0	1	20372
Weekend	0.23	0.42	0	1	642753	0.22	0.41	0	1	20372
VehicleCost	0	0.06	-0.64	0.73	642753	0	0.05	-0.48	0.34	20372
Model Age 5-13 Months	0.73	0.44	0	1	642753	0.72	0.45	0	1	20372
Model Age > 14 Months	0.11	0.32	0	1	642753	0.07	0.26	0	1	20372
#ofCarsSold	2700	2267	300	12063	642753	2877	2217	300	12063	20372
#ofCarsSold*Comp.	8418	11217	0	120960	642753	8411	10303	0	120630	20372
#ofABTFran.in5 m.	6.09	6.93	0	71	642753	7.06	7.51	0	66	20372
PriceVariation1	0.04	0.01	0	0.24	642753	0.04	0.01	0	0.17	20372
PriceVariation2	0.04	0.01	0	0.24	642753	0.04	0.01	0	0.17	20372
PriceVar.2*%Coll.	0.01	0.01	0	0.14	642753	0.02	0.01	0	0.07	20372
ABTAdvertising	2.36	2.37	0	7.5	642753	2.66	2.41	0	7.5	20372
ABTAdv.*Male	1.51	2.21	0	7.5	642753	1.78	2.34	0	7.5	20372
ABTFran.ExtraDist.	12.19	23.95	0	2483	642753	9.32	20.96	0	1412	20372
DealerDistance	5.14	7.73	0	1065	642753	5.4	7.22	0	220.7	20372

Table 3: Summary statistics by *AutobytelFranchise*

Variable	AutobytelFranchise=0 Mean	SD	Min	Max	Obs	AutobytelFranchise=1 Mean	SD	Min	Max	Obs
Volume	292.5	458.25	1	4835	3019	562.87	690.23	2	4496	500
Sales	6.89MM	10.97MM	9000	127.6MM	3019	13.27MM	16.16MM	36368	148.78MM	500
%Autobytel	0.04	0.05	0	1	3019	0.08	0.05	0	0.33	500
%Financing	0.67	0.18	0.05	1	2943	0.67	0.15	0.18	0.97	499
%TradeIn	0.44	0.19	0.01	1	2813	0.36	0.14	0.04	0.72	499
%Same	0	0	0	0.1	3019	0.03	0.04	0	0.2	500
%Black	6.06	7.78	0	79.93	3019	6.09	5.49	0	33.32	500
Cust.Age	45.73	8.21	19	83	3019	44.6	6.28	33	69.5	500
Cust.Income	52920	15461	16573	150000	3019	57820	12061	29877	97232	500
Competition	2.43	2.16	0	23	3019	2.64	2.24	1	18	500

* The low minimum for *Volume* and *Sales* is due to the fact that some dealerships only started reporting to MRI towards the end out our sample period.

Table 4: OLS results†

	(1)	(2)	(3)
Dep. Variable: ln(price)	Full Sample	Full Sample	EndOfMo. = 1
Autobytel	-0.99**	-0.89**	-0.78**
	(0.028)	(0.028)	(0.058)
AutobytelFranchise	-0.5**	-0.45**	-0.46**
	(0.015)	(0.015)	(0.032)
HadTradedIn	0.33**	0.32**	0.3**
	(0.014)	(0.014)	(0.029)
EndOfMonth	-0.34**	-0.33**	
	(0.015)	(0.015)	
Weekend	0.099**	0.11**	0.072*
	(0.016)	(0.016)	(0.034)
VehicleCost	88**	88**	88**
	(0.13)	(0.13)	(0.28)
Model Age 5-13 Months	0.17**	0.17**	0.053
	(0.031)	(0.031)	(0.064)
Model Age > 14 Months	-0.32**	-0.34**	-0.59**
	(0.053)	(0.053)	(0.12)
Income		-0.015**	-0.013**
		(0.0014)	(0.0029)
Income^2		0.00012**	0.00011**
		(7.5e-06)	(0.000015)
%CollegeGrad		-0.23*	-0.54**
		(0.093)	(0.2)
%LessHighSchool		0.34**	0.11
		(0.13)	(0.27)
%HouseOwnership		-0.26**	-0.36**
		(0.045)	(0.095)
MedianHouseValue		-0.0026**	-0.0025**
		(0.00013)	(0.00026)
%Professional		0.39**	0.7*
		(0.14)	(0.29)
%Executives		0.0078	0.1
		(0.14)	(0.3)
%BlueCollar		0.085	0.18
		(0.1)	(0.21)
%Technicians		0.58+	1.1
		(0.34)	(0.7)
CustomerAge		0.0043**	0.005**
		(0.00062)	(0.0013)
Age> 64		-0.2**	-0.24**
		(0.033)	(0.07)
Female		0.2**	0.15**
		(0.014)	(0.03)
%Asian		-0.43**	-0.16
		(0.093)	(0.2)
%Black		0.31	-0.29
		(0.32)	(0.66)
%Hispanic		1.1**	1.5**
		(0.1)	(0.22)
Female*Over64		0.11*	0.079
		(0.047)	(0.099)
%Black*MedianHouseVal.		0.0027**	0.0042**
		(0.00078)	(0.0016)
Constant	1002**	1002**	1003**
	(0.043)	(0.09)	(0.19)
Observations	663125	663125	148384
Adj. R-squared	0.975	0.975	0.976

+ All coefficients are multiplied by 100. * significant at 5%; ** sign. at 1%. Robust standard errors in parentheses.
† Unreported are car, month, and region fixed effects.

Table 5: Subsegment results[†]

Autobytel∗...		Autobytel∗...	
Basic Large	-0.45 (0.39)	Lower Midsize	-1.4** (0.14)
Compact Pickup	-1.8** (0.18)	Luxury SUV	-0.46* (0.19)
Compact SUV	-0.67** (0.07)	Mid Sporty	-1.0** (0.14)
Compact Van	-0.55** (0.086)	Mini SUV	-1.3** (0.1)
Entry Compact	-1.8* (0.8)	Near Luxury	-0.33** (0.077)
Entry Sporty	-3.1** (1.0)	Premium Compact	-1.5** (0.097)
Fullsize Pickup	-1.4** (0.33)	Premium Sporty	0.21 (0.27)
Fullsize SUV	-0.85** (0.15)	Traditional Luxury	-0.76 (0.49)
International Luxury	-0.62** (0.12)	Upper Midsize	-1.1** (0.061)

[*] significant at 5%; ** significant at 1%. Robust standard errors in parentheses.
[+] All coefficients are multiplied by 100.
[†] Specification as in column 2 in Table 4, excluding *Autobytel*, including *Autobytel*∗subsegment interactions.

Table 6: Competition results†

	(1)	(2)
Dep. Variable ln(price)	Full Sample	Full Sample
	ln(Price)	ln(Price)
Autobytel	-0.89**	-0.75**
	(0.028)	(0.049)
ABTFranchise	-0.46**	-0.46**
	(0.015)	(0.015)
# Competing Dealers	-0.029**	-0.027**
	(0.0035)	(0.0035)
Autobytel* # Competing Dealers		-0.051**
		(0.015)
EndOfMonth	-0.33**	-0.33**
	(0.015)	(0.015)
Weekend	0.11**	0.11**
	(0.016)	(0.016)
VehicleCost	88**	88**
	(0.13)	(0.13)
Model Age 5-13 Months	0.17**	0.17**
	(0.031)	(0.031)
Model Age > 14 Months	-0.34**	-0.34**
	(0.053)	(0.053)
HadTradedIn	0.31**	0.31**
	(0.014)	(0.014)
Constant	1002**	1002**
	(0.091)	(0.091)
Observations	663125	663125
Adj. R-squared	0.975	0.975

* significant at 5%; ** significant at 1%. Robust standard errors in parentheses.

+ All coefficients are multiplied by 100.

† Unreported are *CustomerAge, Age>64, %Black, %Black*MedianHouseVal, %Hispanic, %Asian, Female, MedianHHIncome, (MedianHHInc.)^2, %CollegeGrad, %<HighSchool, %HouseOwn., MedianHouseVal., %Professional, %Executives, %BlueCollar, %Technicians*, car, month, and region fixed effects

Table 7: Probit for IV†

Probit: Dep. Var.	Autobytel	AutobytelFranchise
#ABTFranIn5Mi.	0.00102* (0.000511)	0.00553** (0.000291)
PriceVariation1	2.46* (0.981)	-0.24 (0.486)
PriceVariation2	-9.37** (1.1)	2.73** (0.545)
PriceVar2*Coll.	3.73** (1.26)	3.35** (0.687)
#ofCarsSold	0.0000267** (2.38e-06)	0.0000589** (1.34e-06)
#ofCarsSold*Comp.	-3.62e-06** (6.47e-07)	-0.0000114** (3.48e-07)
ABTAdvertising	-0.00099 (0.00275)	-0.0024 (0.00156)
ABTAdvertising* (1-Female)	0.00281 (0.00284)	3.81e-06 (0.00161)
ABTFranExtraDist	-0.00087** (0.000176)	-0.0277** (0.000147)
DealerDistance	0.00343 (0.00030)**	0.00336 (0.00024)**
Income	0.00546** (0.000719)	-0.000771+ (0.000401)
Income^2	-0.0000382** (3.91e-06)	-0.0000104** (2.26e-06)
%CollegeGrad	0.264** (0.0705)	0.186** (0.0402)
%LessHighSchool	-0.0784 (0.0698)	0.019 (0.0344)
%HouseOwnership	-0.0572* (0.0227)	0.0711** (0.0124)
MedianHouseValue	0.000489** (0.0000612)	0.000164** (0.0000366)
%Professional	0.143* (0.068)	-0.27** (0.0398)
%Executives	0.295** (0.0722)	0.203** (0.0412)
%BlueCollar	-0.144** (0.0544)	0.329** (0.0286)
%Technicians	0.819** (0.169)	-0.0869 (0.0961)
CustomerAge	-0.0057** (0.0003)	-0.000767** (0.000167)
Age> 64	-0.175** (0.0191)	-0.0604** (0.00932)
Female	-0.0748** (0.0104)	-0.00991+ (0.00573)
%Asian	0.153** (0.0437)	0.104** (0.025)
%Black	0.125 (0.161)	-0.0595 (0.084)
%Hispanic	-0.323** (0.0542)	-0.233** (0.0275)
Female*Over64	-0.0394 (0.0313)	0.0443** (0.0136)
Black*MedianHouseVal.	-0.000817* (0.000405)	-0.000309 (0.000204)
Constant	-1.74** (0.0549)	-0.874** (0.029)
Observations Pseudo R-squared	663125 0.06	663125 0.10

+ significant at 10% * significant at 5%; ** sign. at 1%. Robust standard errors in parentheses.

† Unreported are *HadTradedIn, EndOfMonth, Weekend, VehicleCost*, model age, month, region dummies, and dummies for missing values in ABTAdvertising and ABTAdvertising*Male.

Table 8: IV results†

Dep. Var. ln(Price)	All Instruments	without #ABTFran-In5Miles	without PriceVar1	without PriceVar2, PriceVar2* College	without #ofCarsSold, #ofCarsSold* Competition	without ABTAdvert., ABTAdvert.* Male
Autobytel	-2.41** (0.897)	-2.69** (0.894)	-2.44** (0.897)	-2.29* (0.902)	-2.14* (0.928)	-2.97** (0.915)
AutobytelFranchise	-1.01** (0.0555)	-1.07** (0.0556)	-1.01** (0.0555)	-1.01** (0.0555)	-1.03** (0.0559)	-1** (0.0556)
HadTradedIn	0.295** (0.0153)	0.292** (0.0153)	0.295** (0.0153)	0.296** (0.0153)	0.297** (0.0154)	0.29** (0.0154)
EndOfMonth	-0.329** (0.0152)	-0.328** (0.0152)	-0.329** (0.0152)	-0.329** (0.0152)	-0.329** (0.0152)	-0.328** (0.0153)
Weekend	0.109** (0.0155)	0.108** (0.0155)	0.108** (0.0155)	0.109** (0.0155)	0.109** (0.0155)	0.107** (0.0155)
VehicleCost	88.2** (0.107)	88.2** (0.107)	88.2** (0.107)	88.2** (0.107)	88.2** (0.107)	88.2** (0.107)
Model Age 5-13 Months	0.165** (0.0314)	0.164** (0.0315)	0.165** (0.0314)	0.165** (0.0314)	0.165** (0.0314)	0.163** (0.0315)
Model Age > 14 Months	-0.347** (0.0516)	-0.348** (0.0516)	-0.347** (0.0516)	-0.346** (0.0516)	-0.346** (0.0516)	-0.349** (0.0516)
Income	-0.0133** (0.00141)	-0.0131** (0.00142)	-0.0133** (0.00141)	-0.0133** (0.00141)	-0.0132** (0.00141)	-0.0133** (0.00142)
$Income^2$	0.000102** (8.20e-06)	0.0001** (8.20e-06)	0.000102** (8.20e-06)	0.000102** (8.20e-06)	0.000102** (8.20e-06)	0.000101** (8.21e-06)
%CollegeGrad	-0.214* (0.0983)	-0.204* (0.0983)	-0.213* (0.0983)	-0.217* (0.0983)	-0.221* (0.0985)	-0.198* (0.0985)
%LessHighSchool	0.451** (0.12)	0.457** (0.12)	0.451** (0.12)	0.45** (0.12)	0.451** (0.12)	0.453** (0.12)
%HouseOwnership	-0.291** (0.0438)	-0.292** (0.0438)	-0.291** (0.0438)	-0.29** (0.0437)	-0.291** (0.0437)	-0.291** (0.0438)
MedianHouseValue	-0.00224** (0.000138)	-0.00221** (0.000138)	-0.00224** (0.000138)	-0.00224** (0.000138)	-0.00224** (0.000138)	-0.00222** (0.000138)
%Professional	0.297* (0.142)	0.289* (0.142)	0.297* (0.142)	0.295* (0.142)	0.289* (0.142)	0.305* (0.142)
%Executives	0.0514 (0.148)	0.0603 (0.148)	0.0519 (0.148)	0.0486 (0.148)	0.046 (0.148)	0.0636 (0.148)
%BlueCollar	-0.0254 (0.0983)	-0.0255 (0.0984)	-0.0252 (0.0983)	-0.0264 (0.0983)	-0.0286 (0.0983)	-0.0204 (0.0984)
%Technicians	0.64+ (0.345)	0.662+ (0.345)	0.641+ (0.345)	0.633+ (0.345)	0.625+ (0.345)	0.671+ (0.345)
CustomerAge	0.00346** (0.000683)	0.00334** (0.000683)	0.00345** (0.000683)	0.0035** (0.000683)	0.00355** (0.000688)	0.00327** (0.000686)
Age> 64	-0.207** (0.0328)	-0.209** (0.0328)	-0.207** (0.0328)	-0.206** (0.0328)	-0.206** (0.0328)	-0.21** (0.0329)
Female	0.185** (0.0155)	0.184** (0.0155)	0.185** (0.0155)	0.186** (0.0155)	0.187** (0.0156)	0.182** (0.0156)
%Asian	-0.265** (0.0938)	-0.254** (0.0938)	-0.265** (0.0938)	-0.266** (0.0937)	-0.263** (0.0937)	-0.264** (0.0939)
%Black	0.35 (0.308)	0.343 (0.308)	0.35 (0.308)	0.353 (0.308)	0.355 (0.308)	0.339 (0.308)
%Hispanic	1.15** (0.0983)	1.15** (0.0984)	1.15** (0.0984)	1.15** (0.0983)	1.16** (0.0984)	1.14** (0.0985)
Female*Over64	0.121** (0.0465)	0.123** (0.0466)	0.121** (0.0465)	0.121** (0.0465)	0.121** (0.0465)	0.122** (0.0466)
Black* MedianHouseVal.	0.00268** (0.000739)	0.0027** (0.000739)	0.00268** (0.000739)	0.00268** (0.000739)	0.00268** (0.000739)	0.0027** (0.00074)
Constant	1002** (0.0936)	1002** (0.0936)	1002** (0.0936)	1002** (0.0936)	1002** (0.0938)	1002** (0.0938)
Observations	663125	663125	663125	663125	663125	663125

+ All coefficients are multiplied by 100. * significant at 5%; ** sign. at 1%. Robust standard errors in parentheses.
† Unreported are car, month, and region fixed effects.

Table 9: Summary statistics for survey data

Variable	Obs	Mean	Std. Dev.	Min	Max
Internet	1752	0.73	0.45	0	1
OBSSite	1752	0.37	0.48	0	1
LikeNegotiating	1752	2.18	1.02	1	4
AfraidTakenAdvantage	1752	2.72	0.98	1	4
NoTimeToShop	1752	2.56	0.84	1	4
DoPriceComparisons	1752	3.47	0.66	1	4
GatherMuchInfo	1752	3.16	0.8	1	4
TriesFindInvoice	1752	3.03	0.88	1	4
ReadCarMagazine	1752	1.87	0.84	1	4
VisitDealerForFun	1752	1.69	0.76	1	4

Table 10: Internet usage by consumer type†

Dep. Variable:	InternetUse	IRSUse
LikeNegotiating	-0.170 (0.039)**	-0.116 (0.035)**
AfraidTakenAdvantage	0.003 (0.038)	0.072 (0.034)*
NoTimeToShop	0.021 (0.045)	0.088 (0.040)*
DoPriceComparisons	0.061 (0.062)	0.003 (0.063)
GatherMuchInfo	0.401 (0.057)**	0.295 (0.056)**
TriesFindInvoice	0.328 (0.048)**	0.196 (0.046)**
ReadCarMagazine	-0.113 (0.048)*	-0.068 (0.043)
VisitDealerForFun	-0.069 (0.053)	-0.051 (0.050)
MedianHHIncome (000s)	0.012 (0.008)	-0.000 (0.008)
$(\text{MedianHHInc.})^2$	-0.00006 (0.00005)	0.00002 (0.00005)
%CollegeGrad	0.822 (0.536)	-0.046 (0.486)
%LessHighSchool	-0.091 (0.623)	-0.356 (0.610)
%HouseOwnership	-0.254 (0.245)	-0.096 (0.223)
MedianHouseVal. (000s)	-0.043 (0.059)	-0.056 (0.054)
%Professional	-0.841 (0.847)	0.369 (0.764)
%Executives	-0.441 (0.841)	-0.775 (0.770)
%BlueCollar	0.147 (0.583)	-0.311 (0.550)
%Technicians	-0.666 (1.963)	2.614 (1.759)
CustomerAge	-0.222 (0.046)**	-0.121 (0.042)**
Age> 64	-0.171 (0.152)	0.024 (0.152)
Female	-0.123 (0.078)	-0.097 (0.072)
%Asian	0.100 (0.334)	0.317 (0.298)
%Black	-0.449 (0.359)	-0.356 (0.364)
%Hispanic	-1.129 (0.526)*	-0.190 (0.493)
Constant	-0.405 (0.512)	-1.177 (0.474)*
Observations	1752	1752

* significant at 5%; ** significant at 1%; + significant at 10% level. Standard errors in parentheses.

+ All coefficients are multiplied by 100.

† Response scale on trait variables: 1="Disagree Strongly", 4="Agree Strongly."

Table 11: Dealer cost results[†]

Dep. Variable	(1) vehicle cost	(2) ln(vehicle cost)
AutobytelFranchise	64**	0.0029**
	(4)	(0.00018)
EndOfMonth	-0.26	0.000026
	(4)	(0.00018)
Weekend	-52**	-0.0023**
	(4)	(0.00018)
Model Age 5-13 Months	16*	0.00047
	(8.3)	(0.00036)
Model Age > 14 Months	22	0.0015**
	(14)	(0.0006)
Constant	22217**	10**
	(12)	(0.00053)
Observations	663125	663125
Adj. R-squared	0.966	0.962

[*] significant at 5%; ** significant at 1%
Robust standard errors in parentheses
[†] Unreported: month, region, and car fixed effects.

Table 12: Car switching results†

	(1)	(2)	(3)	(4)
Dep. Variable ln(price)	Full Sample	Full Sample w/ ChangeCar	Full Sample w/ ChangeCar	Full Sample w/ ChangeCar
Autobytel	-0.95** (0.034)	-0.9** (0.028)	-0.9** (0.028)	-0.95** (0.034)
Autobytel*ChangeCar		-0.46** (0.032)	-0.36** (0.039)	-0.46** (0.034)
Autobytel*ChangeMake			-0.7** (0.056)	
AutobytelFranchise	-0.47** (0.015)	-0.47** (0.015)	-0.47** (0.015)	-0.47** (0.015)
SameDealer	0.19** (0.06)			0.19** (0.06)
SameDealer*ChangeCar				-0.046 (0.11)
EndOfMonth	-0.33** (0.015)	-0.33** (0.015)	-0.33** (0.015)	-0.33** (0.015)
Weekend	0.11** (0.016)	0.1** (0.015)	0.1** (0.015)	0.1** (0.015)
Model Age 5-13 Months	0.17** (0.031)	0.17** (0.03)	0.17** (0.03)	0.17** (0.03)
Model Age > 14 Months	-0.34** (0.053)	-0.34** (0.052)	-0.34** (0.052)	-0.34** (0.052)
# Competing Dealers	-0.029** (0.0035)	-0.029** (0.0034)	-0.029** (0.0034)	-0.029** (0.0034)
VehicleCost	88** (0.13)	88** (0.13)	88** (0.13)	88** (0.13)
HadTradedIn	0.31** (0.014)	0.32** (0.013)	0.32** (0.013)	0.32** (0.013)
Constant	1002** (0.091)	1003** (0.089)	1003** (0.089)	1003** (0.089)
Observations	663125	683760	683760	683760
Adj. R-squared	0.975	0.975	0.975	0.975

* significant at 5%; ** significant at 1%. Robust standard errors in parentheses.

+ All coefficients are multiplied by 100.

† Unreported are *CustomerAge, Age>64, %Black, %Black*MedianHouseVal, %Hispanic, %Asian, Female, MedianHHIncome, (MedianHHInc.)*^{2}*, %CollegeGrad, %<HighSchool, %HouseOwn., MedianHouseVal., %Professional, %Executives, %BlueCollar, %Technicians*, car, month, and region fixed effects.

Figure 1: Dispersion of residuals by *Autobytel*