Preliminary and incomplete.
Please do not cite without permission of the authors.

Are Consumers Affected by Durable Goods Makers' Financial Distress? The Case of Auto Manufacturers*

Ali Hortaçsu
Department of Economics, University of Chicago and NBER
hortacsu@uchicago.edu

Gregor Matvos
University of Chicago Booth School of Business
gregor.matvos@chicagobooth.edu

Chad Syverson
University of Chicago Booth School of Business and NBER
chad.syverson@chicagobooth.edu

Sriram Venkataraman
Goizueta Business School, Emory University
Sriram_Venkataraman@bus.emory.edu

January 2010

Abstract

Theory suggests the financial decisions of durable goods makers can impose externalities on their consumers. Namely, the consumption stream that durable goods provide frequently depends on services provided by the manufacturer itself (e.g., warranties, spare parts availability, maintenance and upgrades). Bankruptcy of a manufacturer, or even the possibility thereof, threatens this service provision and as a result can substantially reduce the value of its products to their current owners. We test whether this hypothesis holds in one of the largest durable goods markets, automobiles. We use data on prices of millions of used cars sold at wholesale auctions around the U.S. during 2006-8. We find that an increase in an auto manufacturer's financial distress (as measured by an increase in its CDS spread) does result in a contemporaneous drop in the prices of its cars at auction, controlling for a host of other influences on price. The estimated effects are statistically and economically significant. Furthermore, cars with longer expected service lives (lower mileage or better condition cars) see larger price declines than those with shorter remaining lives. These patterns do not seem to be driven solely by reduced demand from auto dealers affiliated with the troubled manufacturers.

---

* Preliminary and incomplete. Contact information: Hortaçsu: Department of Economics, University of Chicago, 1126 E. 59th St., Chicago, IL 60637.; Matvos and Syverson: University of Chicago Booth School of Business, 5807 S. Woodlawn Ave., Chicago, IL 60637; Venkataraman: Goizueta Business School, Emory University, 1300 Clifton Road NE, Atlanta, Georgia 30322.

1. **Introduction**

Firms' financial decisions have potential externalities on consumers of durable goods. The consumption stream that durable goods provide frequently depends on the product warranties, the availability of spare parts, maintenance and upgrades. For example, a car owner relies on warranties to cover malfunctions early in the car's life, on car parts to be available when the car breaks down, and on the presence of a dealer who can service the car.

As is the case in the car industry, the provision of these and similar services is frequently vertically integrated into the manufacturer.[1] If a car manufacturer were to go bankrupt, they may not honor the warranties and provide parts and services in the future, reducing the consumption of the durable goods owner. In fact, the mere expectation of probable bankruptcy may reduce the expected value of durable goods to a forward-looking consumer. Therefore, as firms experience financial distress they impose potentially large externalities on those who own their goods.

Even though these externalities are potentially important and large, we have little empirical evidence on the relationship between firms' financial distress and the value of durable goods. Since durable goods represent a significant fraction of household wealth, it is important to understand this relationship. Automobiles, the subject of our study, account for about 5 percent of consumption in the US. Vehicles are the nonfinancial asset most commonly held by households and represented roughly 3 percent of US household wealth in 2007 (Bucks et al. (2009)). Any variation in the value of these assets can expose households to wealth and consumption shocks.

[1] Provision of car warranties is generally vertically integrated into the manufacturer, who bundles the warranty with the car. Vertical integration may be natural in this case; it solves the asymmetric information problem present because car manufacturers are best informed about likely future claims on the cars they make. Furthermore, it effectively makes manufacturers the residual claimants on the effort expended toward increasing car durability.

Understanding how firms' financial distress affects owners of durable goods is also critical to understanding firms' financial decisions. Forward-looking consumers understand that financial distress decreases the probability that future warranties will be honored, and service of their car will be available, reducing demand for the cars. Because of these indirect costs of financial distress, firms may curb the amount of debt used in financing despite the large tax advantages of debt financing.[2]

While the literature since Titman (1984) frequently appeals to indirect costs of financial distress to explain why firms use little debt, there is little direct evidence of such indirect costs in general or in durable goods demand in particular (Hotchkiss at al 2008). Studying these effects on demand for goods is empirically challenging because demand shocks affect firms' cash flows, thereby affecting financial distress. For example, suppose we observe a correlation between a durable goods manufacturer's financial condition and the prices of its products. Such a correlation could be caused by shifts in consumers' demands for the firm's products because of financial distress. But the same correlation can be caused by demand shocks: if demand for the firm's products falls for some other reason, this will decrease the manufacturer's profits and weaken its financial position. This generic problem has plagued the literature on the effects of financial distress and indirect costs of bankruptcy, whether these indirect cost are from the consumer, supplier, or employee side.[3]

Our study, besides focusing on an inherently interesting set of products and firms, can avoid many of these identification issues. We study the impact of financial distress on the prices of

---

[2] See Titman (1984) for an early discussion of indirect cost of financial distress; see Graham (2000) on the size of the tax benefits of debt

[3] Despite the lack of evidence, the U.S. Treasury Department certainly believed such indirect cost of financial distress have a large impact on car manufacturers, and through warranties in particular. On March 30, 2009, they announced the Warranty Commitment Program, which guaranteed warranties of new General Motors and Chrysler cars were the manufacturers to go bankrupt. They started the program to "help provide much needed certainty to consumers, and a boost to the auto industry, during the restructuring period." We evaluate this assertion in this paper.

used cars in car auctions conducted by a major car auction house in the United States from January 1st 2006 to November 14, 2008. We compare shifts in the prices of a manufacturer's cars to a measure of that manufacturer's likelihood of bankruptcy. As we discuss below, we believe our data is rich enough to provide sources of identification of the links between cars' values and their manufacturers' financial distress that are unlikely to be driven by reverse causation, where price drops lead to distress rather than vice versa.

A first glance at the data suggests that there may in fact be a link between increases in a manufacturer's financial distress and the value of its used cars. The two panels of Figure 1 compare relative bankruptcy risks and wholesale prices of two manufacturers that experienced considerable financial distress during our sample: Ford and GM. The top panel shows two time series for Ford Motors, both constructed from our data. The dashed line is the price residual of all Ford used cars sold at auction.[4] The solid line shows a measure of Ford's financial distress; a larger value implies more distress. (We will describe in detail below how we measure financial distress.) In order to take out common movements across manufacturers in these series over time, the plotted series are actually the difference between Ford and Honda's respective values. (We chose Honda for no special reason other than it was a reasonably financially stable company throughout the sample.) As is apparent in the figure, during 2008 in particular, as Ford's financial condition worsened relative to Honda's, the relative values of its used cars dropped as well. There is also some indication that as Ford's relative condition was improving in late 2006, its vehicles were rising in relative value. The bottom panel repeats the exercise but replaces Ford with GM, another manufacturer with obvious financial difficulties toward the end of the sample.

[4] We obtain cars' price residuals from a regression that controls for a number of factors that are expectedly invariant to financial conditions. We filter the series through a 12-week moving average in order to reduce the noise in the series.

Again, we see the clear negative correlation in relative prices and financial strength in 2008, but the patterns are less clear prior to that year.

These results are only expository—indeed, our core specifications below don't even use the aggregate, lower-frequency movements shown in the figure to identify the links between distress and used car values—but they serve to motivate the possibility that such links exist.

Looking for such effects in used car auctions holds several advantages over new car markets. Wholesale car markets are very liquid; prices can rapidly adjust to changes in the economic environment. Their participants are knowledgeable about the product and the final demand environment. Their decentralized nature makes them less exposed to strategic pricing. Additionally, one might expect revisions in consumers' beliefs about the quality of a firm's products are more likely to be reflected in the prices of its new products, not its previously produced ones. Simply put, people already know more about the quality of a particular model of a used car than a new version, since the former already has an observable track record. Therefore, any correlation between an automaker's financial distress and the prices of its used cars is more likely to come from the causal effect of distress on prices rather than the opposite direction. Moreover, if the firm's used cars are substitutes for its new ones, then downward revisions in consumers' view of the firm's new cars could actually lead to increases in the relative prices of its used cars. This effect cuts against the mechanism we are testing for, and therefore suggests any results we find might even understate the true impact of distress on prices.

To measure firms' financial distress levels, we use credit default swaps (CDS) spreads. These are securities whose payoff is conditional on the firm defaulting on its debt, so their price reflects the expected probability that a firm enters bankruptcy. Because they are much more liquid than the bonds of the respective companies, they provide the most current measure of companies' financial distress.

Besides focusing on used rather than new car prices, we use several sources of variation in the data to address the identification issues plaguing efforts to measure the effect of financial distress on product demand. Our core specification estimates the car price-CDS spread relationship using variation within detailed model-by-region-by-week categories. For instance, we compare the price difference between a 2005 Ford Focus ST sold at an Atlanta auction on Monday and another 2005 Ford Focus ST sold in Ft. Lauderdale later that same week to the change in Ford's CDS spread during the intervening days. Using high-frequency variation makes it less likely that shifts in consumers' views of a particular manufacturer, which presumably operate at a lower frequency, create simultaneous price shifts and financial distress. That said, we observe the negative correlation between a manufacturer's CDS spread and its used car prices at lower frequencies as well.

Our basic specification indicates that a 1000-point increase in a manufacturer's CDS spread (a large change, but some firms experience even larger ones in the data) drops the average price of its used cars by $68, or about 0.5 percent.

A further testable prediction of our particular setting is that financial distress should not affect all cars to the same degree. Cars with longer expected remaining service lives should expectedly see a greater price drop when a manufacturer risks bankruptcy, as their flow of lost services would be greater. Further, if car owners worry that their warranties will not be honored upon bankruptcy, then the value of these warranties (capitalized into the price of the car) will fluctuate with manufacturers' financial distress. These effects in combination will imply that value of cars with lower mileage should be more affected by financial distress. Further, the prediction about the interaction of the price effect with a car's expected service also implies cars in better mechanical condition will see a greater price decline due to financial distress. In fact, if one of the bundled services that auto manufacturers provide is the availability of spare parts, the highest mileage and worst condition cars could potentially even experience relative price gains when bankruptcy becomes more likely, as these cars are the most likely substitute suppliers of those parts.

We find these patterns in the data. The interaction between a car's mileage and its manufacturer's CDS spread is broadly negative, measured in several ways. Further, there is some evidence of a particular drop in value around the mileage (or age, as applicable) where the car's factory warranty expires. Some price effects are seen at higher mileage levels, suggesting consumers also worry about other bundled services like availability of replacement parts and dealership networks were the firm to go bankrupt. We also find that cars in better condition (as rated by the auction house before sale) see greater value hits. As cars' conditions worsen, the price drop is smaller. In fact, cars in the worst condition—those explicitly rated as salvage value only, and thus essentially usable only for parts—actually see slight price increases when financial distress rises. This pattern is also matched among the highest-mileage cars.

1.1 Related Literature

Our paper touches on the previous literature in two distinct ways. First, it directly contributes to the literature on firm capital structure and the indirect cost of financial distress. Since Titman (1984), indirect cost have been used to rationalize the reluctance of firms to used debt financing despite large tax benefits of debt. In their classic paper, Andrade and Kaplan (1998) study thirty one leverage transactions to try to identify the impact of financial distress on firm value. They estimate financial distress cost to be from 10 to 20 percent of firm value. Our paper is closest to Chevalier (1995a, 1995b) and Chevalier and Scharfstein (1996). They also use transaction level data to study the interaction between financial distress and market outcomes. Their focus is the relationship between supermarkets' financial structures and the pricing decisions in the industry, and in particular the strategic effects of financial distress on entry and markups.

Second, the paper delves into the nature of durable goods markets. Most of the literature on these markets has focused on the interaction between the market for new and used goods, trying to understand the competition a monopolist faces from used goods she sold in the past.[5] Our paper instead highlights the fact that much of the consumption stream from durable goods depends on future commitments from the manufacturer and other providers of complementary services. To understand the behavior of durable goods suppliers and consumers, we have to understand the complex structure of services that accompany the consumption of durable goods.

The paper is structured as follows. In Section 2 we describe the market for used cars and how it is organized though wholesale auctions. We then describe the data we are using and provide descriptive statistics. In Section 3 we discuss our empirical specification. Section 4 presents and discusses our estimates. Section 5 concludes.

2. Institutional Background and Data

Each year, consumers in the United States buy close to 40 million used vehicles, three times the number of new cars sold. In 2008, for example, there were 36.5 million used vehicle sales (~$292 billion in revenues) and 13.2 million new vehicle sales (~$351 billion in revenues). While a small fraction of the used vehicles are traded via private party transactions, the lion's

[5] See Coase (1972), Bulow (1982), and Stokey (1981) for early work on the Coase conjecture.

share of the used car sales is transacted via the dealer networks. Of the 80,000 auto dealerships in the U.S., nearly 60,000 sell only used cars, while the remaining dealers trade both new and old cars.

These dealers acquire the bulk of their used car inventory via weekly used car auctions conducted at various locations. The auctions are typically wholesale buyers only—they exclude the end consumer.[6] In general these transactions occur between purchasing dealers and other firms that are car suppliers. Sellers include other dealers, auto manufacturers, rental car agencies and corporate fleet resellers. Dealers often rely on such auctions to adjust their used car portfolios to changing local market conditions. Manufacturers use these auctions sell fleet and program cars. Car rental agencies use these auctions to trade-in their used cars before they get out of factory warranty. Sellers may also be financial institutions who use the wholesale auction to reduce their inventory of program and repossessed cars.

The top five auctioneers cumulatively command an approximately 80 percent market share in the US. While each auctioneer varies in terms of regional distribution and size of operations at each location, physical auction sites managed by major auctioneers are quite large. Each can have between ten and one hundred lanes where automobiles are wheeled through as auctions take place.

Our wholesale auction data comes from a large multinational auctioneer. The firm is the world's largest provider of vehicle remarketing services and is one of the largest wholesale automobile auctioneers in the US, operating eighty-three geographically dispersed auction sites. We use data on over 6 million successfully completed transactions from January 1, 2006 through November 14, 2008. The total value of these sales was about $89 billion (with an average transaction price of $13,000 per car). The auctioneer runs one or two auction sessions per week

[6] Only licensed buyers and sellers who register with the auctioneer can participate in the auction.

at each site, each lasting approximately five hours. Our auctioneer's sites are quite large (see Figure 2a). Table 3 lists select sites and their respective traded volumes. They vary in size from twelve to ninety-eight lanes as well as in their volume of successful transactions.

On average about 3000 cars sell at each auction location in a given day. Buyers can inspect the car the parking lot prior to the auction session. Each car is provided with a car condition report issued by the auctioneer. This and other vehicle details are prominently displayed in the windshield of each vehicle. Professional auctioneers lead the bidding process, often in the presence of the seller representative (see Figure 2b). When bidding ends, the auctioneer consults the seller's representative or some previously communicated reservation price to determine whether the winning bid is accepted or rejected. Sold or not, the car is then wheeled out and a new vehicle is wheeled in. The entire process takes about thirty seconds per car. Sometimes cars that aren't sold are wheeled back in later in the day. Others are re-auctioned on a future date or even transferred to another site. We observe in the data how many times a car was wheeled in at any auction location before it is sold, as well as sequence in which it was wheeled in (run number).

For buyers and sellers who cannot travel to the physical auction site, the firm also uses a proprietary web-based technology that enables both sides of the market to participate in the live physical auctions via real-time audio and video (Figure 2c). Physical auction lanes are equipped with video cameras that allow online users to view the vehicle as it gets wheeled in, observe the physical bidding activity and place their bids via the web. Online users' bids are displayed on the screen located in the physical lane. Large seller consignors like manufacturers and financial institutions can also chose to sell their vehicles via an "upstream" channel that is operated and managed by our market maker. This service gives sellers the ability to remarket their inventory earlier in the remarketing cycle than physical auction lanes. Buyers save on time and travel expenses with desktop access to “Bid or Buy Now” from the largest nationwide selection of wholesale inventory available. Any unsold cars are moved to the physical auction site and sold through the original process.

In our data we know if the winning bid was placed by an online bidder or in-lane bidder or if the car were purchased in the upstream channel. As you can see from Table 3 approximately ninety percent of the transacted cars were sold to in-lane bidders, eight percent via the upstream channel, and the remaining to online bidders. Sometimes consignors restrict their sales to select buyers only, referred to as “closed” sales. Closed marketplaces often serve to benefit a manufacturer’s franchise dealer network. Unrestricted or open auctions attempt to allow for maximum buyer participation. Seventy-five percent of the transacted cars in our data were sold in unrestricted auctions (Table 3).

Sixty-seven percent of the completed transactions are fleet/lease sales, twenty-eight percent factory owned sales, and five percent are dealer-to-dealer sales (Table 3). Each automobile is identified by manufacturer issued unique vehicle information number (VIN). For each VIN we collected information on a large set of vehicle characteristics including car make (Ford, Toyota, Honda, etc.), model (Taurus, Explorer, Altima, etc.), body style (SUV V6, Midsize 4dr V6, 1500 Pickup V12, etc.), and model year. Our data also include the odometer mileage reading and quality condition of each vehicle as certified by the market maker. See Table 2 for details on the quality rating scale.

We obtain the daily credit default swap spreads (CDS) time-series Thompson Financial DataStream for all publicly traded automobile manufacturers during the corresponding time period as our auctions data. Figure 2 plots the CDS time series for four manufacturers: General

Motors, Ford, Honda and Toyota. The prices are in basis points; which can be interpreted under risk neutrality as default probability: e.g. a CDS of 1000 basis points corresponds to 10% default probability.

We then match the CDS series with the manufacturer identities and time-series of the transactions in the auction database.[7] The matching of CDS data and transactions yields a matched database containing 6,188,759 auto sales. Table 4 contains the descriptive statistics of select variables for our final matched data. The data reflect significant variation in price (mean = \$13,062, median = \$12,300, and s.d. = \$7560) and CDS (mean = 643.1 and s.d. = 856.1). The cars vary by mileage, age, and quality condition—from relatively pristine to useful only for salvage. Table 5 describes the price and CDS variation by quality condition (with 0 being salvage ready and 5 being very good), while Table 6 contain descriptive statistics by mileage tiers.[8] As expected, transacted prices fall with quality and age. However, we should note there exists significant variation in the cross-conditions of these two variables (i.e. there is significant mileage variation within quality tiers, and quality variation within mileage tiers).

3. Empirical Specification

Our core specification to measure the effect of financial distress on used cars' values is the following:

$$\mathrm{p}_{\mathrm{ijklt}} = \beta \mathrm{CDS}_{\mathrm{it}} + \mathrm{X}_{\mathrm{ijklt}}\Gamma + \mathrm{a}_{\mathrm{ijkT}} + \varepsilon_{\mathrm{ijklt}},$$

[7] This yields CDS series for the vast majority of brands in our data, including Acura, Audi, BMW, Buick, Cadillac, Chevrolet, Chrysler, Daewoo, Dodge, Ford, Geo, GMC, Honda, Hummer, Hyundai, Infiniti, Isuzu, Jaguar, Jeep, Land Rover, Lexus, Lincoln, Mazda, Mercedes Benz, Mercury, Mini, Mitsubishi, Nissan, Oldsmobile, Plymouth, Pontiac, Porsche, Saab, Saturn, Scion, Suzuki, Toyota and Volkswagen.

[8] We used the empirical mileage distribution to generate twenty non-overlapping mileage bins and classify each car as being in one of twenty bins based on its odometer reading. We use these bins in some of the specifications below.

where i indexes manufacturer; j indexes car model, trim, and model year (we will refer to any unique combination of i and j as a "car type"); k indexes auction location (which in most specifications will be one of eight regions in the US), l indexes the specific auction at which the car is sold, t indexes day, and T indexes week. Our dependent variable is p_{ijklt}, though we will also use below a normalized price that divides the transacted price by the average sales price of the car type throughout the entire sample. CDS_{it} is the manufacturer credit default swap spread in period t, and β is the coefficient of interest—the estimate of the effect of manufacturer CDS on the price of used cars. The vector X_{ijklt} contains other controls describing the car and auction characteristics. a_{ijkT} is a car type-region-week fixed effect.

The car-type-region-week fixed effects control for a great number of potentially confounding influences on car prices that might be spuriously correlated with CDS spreads or reflect the impact of reverse causation. This includes fundamental heterogeneity across car types, region-specific demand and supply shocks for particular vehicles or types of vehicles, and aggregate movements over time. Hence the specification estimates the relationship between car prices and CDS changes only from changes in the auction prices of a given (detailed) type of car within a given region and week.

Intuitively, the regression compares within region-week price differences in cars of manufacturers undergoing financial distress (reflected as an increase in their CDS_{it}) with contemporaneous price changes of cars sold in the same region that are made by more financially stable firms. (Of course, stability per se is not necessary for identification of β; all that is required is differential changes in spreads across manufacturers.) The regression estimate of β simply correlates the differential changes in models' auction prices with the differential changes in the respective manufacturers' CDS spreads, controlling for any fixed or variable effects on prices as captured in a_{ijkT} or X_{ijklt}.

Our choice to limit our identifying CDS price variation to within-week movements may in some ways be overly restrictive, especially if the effects of changes in financial distress take some time to diffuse into wholesale markets. However, restricting ourselves to high-frequency variation in CDS spreads and prices increases the likelihood that we capture the causal impact we seek to measure. It eliminates the possibility that lower-frequency shifts in consumers' views toward a particular manufacturer that both reduce the manufacturer's used car prices and raise its likelihood of bankruptcy are driving our results.

We conduct several additional tests for distress-driven price effects. Each involves specifications that interact the CDS effect with measures that plausibly reflect the extent to which an owner could expect future flows of bundled services. That is, they have the following canonical form:

$$\mathrm{p_{ijklt}} = \beta \mathrm{CDS_{it}} + \gamma \mathrm{Z_{ijklt}} + \delta\left(\mathrm{Z_{ijklt}} * \mathrm{CDS_{it}}\right) + \mathrm{X_{ijklt}}\Gamma + \mathrm{a_{ijkT}} + \varepsilon_{\mathrm{ijklt}},$$

where Z_{ijklt} is a car-specific measure of the expected future flows of services. If increased financial distress decreases the expected availability of these services, financial distress should have a larger effect on cars with greater remaining service lives. If service life is positively correlated with Z_{ijklt}, then this would imply $\delta < 0$.

We use multiple measures for Z_{ijklt}. One is a set of indicators for 20 equal-sized mileage quantiles. This allows us to flexibly capture the differential impact of financial distress across cars of various mileage levels. Two focus on the provision of warranty services in particular (we have gathered data on the coverage period of the cars' original factory warranties). One is an indicator for cars under warranty. This is equal to one if a car meets both its warranty's mileage and age requirements at the time of the auction (e.g., it has under 36,000 miles and is less than 3 years old) and zero otherwise. Specifications estimated using this indicator reflect the average difference in CDS effects on prices for cars that are in and out of warranty. Another warranty variable measures the fraction of the original warranty remains on the car. This is computed as the minimum of two ratios: the difference between the warranty mileage limit and the car's current mileage, divided by the mileage limit; and the difference between the warranty age limit and the car's current age, divided by the age limit. Each of the ratios is defined to be zero if the car's current mileage (age) is greater than the warranty limit. This specification imposes an effect of financial distress on prices that linearly changes as a car gets closer to the expiration of its warranty. Still another measure of Z_{ijklt} that we use is a set of indicators for the auction house's condition rating for cars (these are described in Table 2). Low values for the rating indicate cars in poorer conditions, and as such those with shorter expected service lives than other cars of the same make, model, trim level, and model year.

Because our CDS measures do not vary across cars made by the same manufacturer and may also be serially correlated, we cluster all standard errors reported below by manufacturer-month. This allows an arbitrary error correlation structure across cars made by the same manufacturer as well as intertemporally within months.

4. Results

4.1. Baseline Specification

The patterns seen in Figure 1 suggest that there are negative correlations between manufacturers' CDS spreads and the values of their used cars. However, to try to eliminate as many confounding factors as possible, we will focus below on our more saturated specification that looks at differences within car type-region-week cells.

The results from the first specification of this type are shown in Table 7, column 1. Not surprisingly, given the extent of our included controls, our model does very well explaining the substantial variation in car prices in our sample. The adjusted R^2 is 0.986. The coefficient on manufacturer CDS is -0.068, with a standard error of 0.021. The coefficient implies that a 1000 basis point increase in CDS spread leads to a drop in a car's value of $68. That is roughly a 0.5 percent drop in value off the average $13,062 price of a used car in our sample.

Note that besides the fixed effects, the specification controls for a number of other possibly confounding factors in the data. We include a set of dummies for mileage bins to flexibly capture the effect of mileage on prices. Not surprisingly, average prices decline in mileage. In fact, prices monotonically decrease as one moves from low to high mileage bins. We include dummies for the auction format the car was sold under (this does vary within a day at specific auction locations) and the number of times the car was wheeled through the auction lane, which could be a function of demand or supply factors affecting car price.

One potential worry with our results is that car owners adjust the supply of cars in these auctions when they are affected by the same shocks as the manufacturer. For instance, perhaps rental car companies that have close ties with a particular manufacturer suffer financial shocks that are correlated with those of the manufacturer and are forced to respond by liquidating inventory. This would induce a negative correlation between CDS spreads and prices arising not simply from the manufacturer's financial distress but from supply effects as well. We control for supply effects using two different measures. The first supply control is the number of cars of the same model, trim, and model year being sold on that day in the particular auction location. The second measures how many cars of same model, trim, and model year had been sold up to this point in the sample at the same location.

The specification in Table 7 column 1 uses the car's auction price as a dependent variable. This imposes that the effect of CDS movements has the same absolute size across all cars. Yet it's possible that the absolute effect could be related to the price level of the car rather than independent of it. To account for this possibility, we also run the same specification using as the dependent variable the car's auction price normalized by the average price of its car type (make, model, trim, and model year) throughout the entire sample. In this case, the coefficient on CDS can be interpreted as the size of the effect of financial distress in proportion to the average price level of a car's type.

The results from this specification are shown in Table 7 column 2. Here, the coefficient on manufacturer CDS is -6.07×10^{-6} (s.e. = 1.30×10^{-6}). This implies that for each 1000 basis point increase in CDS spreads, a car's price falls by roughly 0.6 percent. This is essentially the same as the implied percentage change in price from the previous specification using dollar-valued prices. Thus our estimated effects are apparently consistent across price measurements.

4.2. Interactions with Expected Service Lives

An additional prediction of the financial distress/bundled services link is that the impact of financial distress should vary across cars with different services lives. For example, cars with lower mileage have warranties, and within cars with warranties, have more coverage remaining. They also have longer expected service lives even outside of warranty, so the value of bundled services that their manufacturer provides is also greater. These factors suggest that owners of cars with lower mileage should be more exposed to the fluctuations in manufacturers" financial distress the manufacturer. We test for heterogeneous effects in cars' mileage by estimating a specification that interacts our categorical mileage dummies with the manufacturer's CDS spread.

As discussed in the previous section, we test for these effects in several ways. One is to include a set of dummies for each one of twenty mileage quantiles. The quantile boundaries are selected to equate the number of cars in each category (ties result in slight differences across categories in practice).

Table 7, column 3 shows the results of this exercise. We also present the implied relationship between the effect of CDS and car mileage graphically in Figure 4. We can see that, with the exception of the first mileage bin (the excluded category and thus reflect in the main CDS coefficient), the estimated total effects of the interactions are significantly negative for the lowest 14 mileage bins. This corresponds to cars with no more than 50,035 miles. The point estimates initially become more negative (i.e., larger in magnitude) as mileage increases, but after reaching an interacted effect of -0.154 in the 8th bin (this implies a \$154 dollar drop in price for a 1000-point rise in CDS spreads; the bin has an average mileage of 25,766 miles), they begin to become more positive. They continue to rise throughout the rest of the mileage bins, and actually become significantly positive by the 17th bin and remain so after.

These results are echoed when we use normalized prices instead of price levels, as seen in Table 7, column 4. There are negative and significant impacts of CDS on cars in the first 15 mileage bins (applying a test for the base effect plus interaction coefficients, the 2nd and 3rd bins are only significant at the 10 percent level). The largest price impact is seen for the 9th bin, as in the price levels specification, after which the interaction becomes more positive. Also in line with the results above, the maximum estimated impact is a 1 percent price drop per 1000 point

CDS increase; the $154 effect in the levels specification is about 1.2 percent of the average price in the sample. Further, as above, cars in the highest mileage bin see significant price gains when their manufacturer's CDS rise.

These mileage results help address the alternative hypothesis that time varying perceptions of a manufacturer's car quality drive both the manufacturer's CDS spreads and car prices simultaneously. For this alternative story to be true, these innovations in quality perceptions would have to disproportionally affect lower mileage cars, and in particular cars that are under their warranty thresholds. In other words, people's perceptions of the quality of, say, a 2003 Ford Focus with 20,000 miles would have to change very frequently and be highly correlated with Ford's financial condition, while at the same time, there would be virtually no quality updating for a 2003 Ford Focus with 90,000 miles.

We estimate three further checks on our heterogeneous-effect findings across cars' remaining service lives. Two look especially at the role of warranties. In one, we define an indicator variable denoting if a car is still under original factory warranty. To be defined as such, it must meet both the mileage and age requirements of the warranty. We then test whether the price effects of CDS increases are in fact larger in magnitude (i.e., more negative) for cars under warranty than those out of warranty. In the second warranty check, we compute the fraction of the warranty remaining for a car. (The minimum fraction between the mileage and age limits is used; cars out of warranty receive a value of zero.) We interact this variable with CDS to see if cars with different degrees of remaining warranties see different price effects. The third specification interacts CDS with a measure of the car's physical quality. As mentioned above, the auction house grades cars' conditions on a six-point scale, ranging from 0 (useful for salvage only) to 5 (no or minor defects). This specification tests whether financial distress has different impacts across cars of varying quality by interacting our CDS spread measures with both the car's condition score and its mileage band.

The results using the dichotomous in-warranty indicator are in Table 8 Column 1. The main effect of CDS, and therefore the average impact for cars that are *out* of warranty, has a coefficient of -0.006 (s.e. = 0.025). Thus the specification implies a negative but insignificant impact on these cars' prices. The interaction, however, has a negative and significant coefficient. The full implied effect of CDS has a coefficient of -0.062 (s.e. = 0.020). This is roughly the size of the main effect estimated above. This is consistent with the threat of the loss of warranty coverage being an important driver of the CDS price effect.

The second warranty specification, which interacts a measure of the fraction of the factory warranty that remains on the car with the CDS spread, is in Table 8 column 2. The estimated coefficient on the CDS main effect again represents the average impact for cars that are out of warranty and is a statistically insignificant -0.01. The coefficient on the interaction of CDS and the fraction of warranty remaining, however, is -0.129, and is significant at the 10 percent level. The fully interacted effect of CDS is -0.139 (s.e.=0.05), and this is significant at the 1 percent level. This result implies that a car with its full factory warranty remaining (i.e., its fraction is one) would see a price hit of $139 per 1000 point CDS change, and this then linearly declines until the warranty expires at an insignificant $10 per 1000 point change. This result therefore has the intuitive property that the effect of CDS on prices falls the shorter is the remaining period over which the warranty applies and during which the car will be operational.

The results of the exercise with the condition rating interaction are in Table 8, Column 3. The main CDS effect, which corresponds to the impact on cars in condition category 0 (salvage only) is actually positive and significant. This is consistent with these cars, as a store of available replacement parts, actually becoming more valuable when the manufacturer faces financial distress. However, the size of the coefficient, 0.463, implies what is probably an implausibly large point estimate of a $463 price gain when CDS spreads rise by 1000 basis points. Such cars represent less than 0.3 percent of the sample, however. Category 1 (poor condition) cars also have a positive total effect of CDS, but this has a more modest (and realistic) coefficient of 0.121. The interactions between categories and CDS continue to fall monotonically as the car's condition improves, as would be expected if better condition cars have longer expected service lives. Those in the best 3 condition categories (3, 4, and 5) all experience significantly negative price effects when CDS rises, on the order of $56 to $78 price drops per 1000 point CDS increase.

Each of these alternative specifications is consistent with the notion that the negative impact of a manufacturer's financial distress is larger for those cars with longer expected remaining service lives, and therefore a greater future need for bundled services. Further, there seems to be a special role for warranty coverage in explaining these effects.

4.3. Robustness Checks

We conduct tests to probe the robustness of our results. To see if, despite all of our controls, our results reflect a spurious correlation between a manufacturer's CDS spread and its used car prices, we conduct a "placebo"-type test. That is, we run our basic specification after having randomly reassigned manufacturers' CDS series among one another. In particular, Ford and GM, which experienced CDS growth in 2008 far beyond that of other companies, are assigned the CDS series of Mitsubishi and Toyota. Of course, two more stable manufacturers, Hyundai and Mitsubishi, had, respectively, Ford and GM's CDS values reassigned to them. This placebo specification therefore compares the auction prices of a manufacturer's cars to the CDS prices of another manufacturer. Since reassignment should expectedly destroy any causal link, the coefficient on CDS in this specification should be informative.

The result of this exercise (using the same set of controls as in Table 7 column 1) are shown in Table 9. The coefficient on CDS is positive and insignificant. Hence it appears that the CDS-price correlations we observed above were tied to within-manufacturer relationships of product values and financial distress.

Our next robustness check investigates whether *dealers'* (i.e., auto retailers) financial distress, not the preferences of final demanders for bundled services, actually drives the relationship between used car prices and manufacturers' CDS spreads. Namely, if dealers become more concerned about their own business prospects when the manufacturer with whom they are affiliated experiences financial distress, this may reduce their demand for used autos. Moreover, since dealers disproportionately purchase used cars of the same makes that their affiliated manufacturer producers, this could lead to a decline in the prices of that manufacturer's used cars. While one might imagine this is another way a manufacturer's financial decisions can have external effects, it is not the consumer-driven bundled-services channel that is of interest to us here.

To see whether this dealer based-mechanism is driving our results, we take advantage of the fact that our data contains the full name of the winner of every auction. These are nearly always car dealerships, as perusal of the names makes clear. Since dealerships that are affiliated with manufacturers (i.e., those that sell new cars, not just used ones) almost invariantly have the name of the make(s) that they sell new in their name, we can tell when, say, a Ford (or Mercury, Lincoln, or Mazda—all makes that Ford owns partially or outright) dealer buys a used car. If the dealer-based mechanism just described is driving our results, we should expect that Ford-affiliated dealers are less likely to buy Ford cars when Ford's CDS rises. We test whether or not this is true for dealers affiliated with the two companies that experienced, by some distance, the greatest amount of financial distress during our sample: Ford and GM.[9]

We do so by estimating a similar specification to our benchmark regression above, with a few exceptions. First, most obviously, the dependent variable is now an indicator equal to one if a Ford dealer (GM dealer, in the GM regression) buys the car. Second, we restrict the sample to only cars with a Ford (GM) make. We keep the saturated fixed effect structure from before. Therefore we are testing whether Ford- affiliated (GM-affiliated) dealers are less likely to buy a used car with a Ford (GM) make when Ford's (GM's) CDSs are high, controlling for the average probability across all sales of a particular car type in a region-week. If the dealer-based mechanism is important, we should find a negative and significant coefficient on CDS in this linear probability model.

The results of this estimation are in Table 9, Columns 2 and 3. First off, the coefficient in the GM equation is positive and significant: GM dealers are, if anything, more likely to buy GM make used cars when GM's CDS rises. Any such effect is pretty small, however. The coefficient implies a 1000-point increase in CDS raises the probability that a GM dealer wins an auction for a GM car by 1.55 percentage points. In the entire sample, 31.6 percent of GM cars are won by a GM-affiliated dealer (most of the rest are won by used-car specialists, though it is not uncommon for new car dealers to purchase across makes when buying used). Thus even a large CDS change doesn't move the probability of purchase far from the baseline. The

[9] Chrysler was of course having serious troubles during much of our sample. However, they were sold to the private equity firm Cerberus in early 2007, well before the financial crisis began and CDS spreads began to rise. There were no Cerberus CDSs in the market, so we have no way to correlate the manufacturer of Chrysler's financial condition with the prices of its used cars. Thus we dropped all Chrysler cars from our sample from 2007 on.

coefficient in the Ford equation is negative, which is more consistent with a dealer-based mechanism being at work. However, the estimate is marginally statistically significant and is again small in magnitude. A 1000-point increase in Ford's CDS reduces the probability that a Ford-affiliated dealer wins an auction for a Ford-make used car by 1.79 percentage points. On average, however, 38.1 percent of Ford cars are bought by Ford dealers. Thus the likelihood of purchase drops only about 4 percent. It is difficult to know the implied price effect of this reduction without knowing more about the supply of other bidders and their valuations, but this does not seem to be a clear driver of our results above, particularly in light of the GM results.

5. Conclusions

We have shown that durable goods manufacturers' financial decisions can impose externalities on their consumers. Firms' financial decisions therefore can impact real outcomes, in this case the consumption of durable goods, and are not neutral in the spirit of the Modigliani-Miller theorem (1958). The proposed channel through which financial distress of manufacturers imposes externalities is that default can threaten the stream of complementary services (e.g., warranties, spare parts availability, maintenance and upgrades) that the manufacturer provides. As a result, shifts in financial health can impact the value of the manufacturer's products to their current owners.

We find evidence that this does in fact hold true for auto manufacturers. Using wholesale auction price data for millions of used cars sold in the U.S. during 2006-8, we show that an increase in an auto manufacturer's financial distress (as measured by an increase in its CDS spread) results in a contemporaneous drop in the prices of its cars at auction, controlling for a host of other influences on price. The estimated effects are statistically and economically significant. A 1-point increase in CDS spread results in a 6.8 cent drop in prices. This implies that a 1000 basis point movement in CDS spreads causes a price reduction of $68, about 0.5 percent of the average sales price in the sample.

Furthermore, cars with longer expected service lives (lower mileage or better condition cars) see larger price declines than those with shorter remaining lives. This is consistent with manufacturers' provision of bundled services being an important component of the value of a durable good. There seems to be in particular an important role of warranties in this regard. Additionally, there is some evidence that parts availability might also move prices. High-mileage and low-quality cars actually see price increases when their manufacturer experiences financial distress, and these vehicles might actually be net suppliers of parts rather than net demanders.

We show that these results are robust across a number of specifications with various measurement strategies. They also do not appear to reflect the reduced demand from dealers affiliated with manufacturers experiencing financial distress, but rather the impact on final consumers of the potential loss of a flow of bundled services.

This drop in car demand from financial distress also implies potentially large cost of indirect cost of financial distress for car manufacturers. We hope that our results will motivate future research into the effect of financial distress on new car sales, which has been the topic of much discussion recently given the policy environment, and was explicitly the motivation behind the U.S. Treasury's Warranty Commitment Program.

References

Andrade, Gregor and Kaplan, Steven N., 1998, How Costly Is Financial (Not Economic) Distress? Evidence from Highly Leveraged Transactions That Became Distressed, The Journal of Finance, Vol. 53, No. 5, 1443-1493.

Bertrand, Marianne, Duflo, Esther and Mullainathan, Sendhil, 2004, How Much Should We Trust Differences-in-Differences Estimates? Quarterly Journal of Economics, Vol. 119, No. 1, 249-275.

Bucks, Brian K., Kennickell, Arthur B., Mach, Traci L. and Moore, Kevin B., 2009, Changes in U.S. Family Finances from 2004 to 2007: Evidence from the Survey of Consumer Finances, Federal Reserve Bulletin, vol. 95, A1-A55.

Bulow, Jeremy I., 1982, Durable-Goods Monopolists, The Journal of Political Economy, Vol. 90, No. 2, 314-332.

Chevalier, Judith A., 1995a, Do LBO Supermarkets Charge More? An Empirical Analysis of the Effects of LBOs on Supermarket Pricing, The Journal of Finance, Vol. 50, No. 4, 1095-1112.

Chevalier, Judith A., 1995b, Capital Structure and Product-Market Competition: Empirical Evidence from the Supermarket Industry, The American Economic Review, Vol. 85, No. 3, 415-435.

Chevalier, Judith A., Scharfstein, David S., 1996, Capital-Market Imperfections and Countercyclical Markups: Theory and Evidence, The American Economic Review, Vol. 86, No. 4, pp. 703-725.

Coase, Ronald H., 1972, Durability and Monopoly, Journal of Law and Economics, Vol. 15, No. 1 , 143-149.

Graham, John R., 2000, How big are the tax benefits of debt?, Journal of Finance, Vol 55,1901-1941.

Hotchkiss, Edith S., John, Kose, Mooradia, Robert M, and Thorburn, Karin S., (2008) Bankruptcy and The Resolution of Financial Distress, Handbook of Corporate Finance Empirical Corporate Finance, Vol 2.

Modigliani, Franco, Miller, Merton, 1958, The Cost of Capital, Corporation Finance and the Theory of Investment, American Economic Review, Vol. 48, No. 3, 261–297.

Stokey, Nancy L., 1981, Rational Expectations and Durable Goods Pricing, The Bell Journal of Economics, Vol. 12, No. 1, 112-128.

Titman, Sheridan, 1984, The effect of capital structure on a firm's liquidation decision, Journal of Financial Economics 13, 137-151.

Table 1
Most Common Car Characteristics

The table presents the most common car characteristics by different variables in our sample. The % of Obs refers to the % share of the category among observations for which information was available.

Brands				Models			
Rank	**Car Make**	**# of Obs.**	**% of Obs.**	**Rank**	**Car Make**	**# of Obs.**	**% of Obs.**
1	FORD	1,387,982	22.43	1	TAURUS	227,158	3.67
2	CHEVROLET	982,143	15.87	2	EXPLORER 4WD V6	123,892	2.00
3	NISSAN	351,425	5.68	3	IMPALA	118,306	1.91
4	TOYOTA	313,965	5.07	4	ALTIMA	112,353	1.82
5	PONTIAC	285,381	4.61	5	GRAND PRIX	108,419	1.75
6	JEEP	255,400	4.13	6	FOCUS	99,004	1.60
7	DODGE	216,632	3.50	7	F150 PICKUP 4WD V8	97,916	1.58
8	HONDA	199,190	3.22	8	MALIBU V6	66,717	1.08
9	B M W	170,190	2.75	9	F150 PICKUP 2WD V8	65,494	1.06
10	HYUNDAI	162,162	2.62	10	MUSTANG V6	64,639	1.04

Model Year				Category			
Rank	**Year**	**# of Obs.**	**% of Obs.**	**Rank**	**Category**	**# of Obs.**	**% of Obs.**
1	2006	1,278,944	20.67	1	SUV	1,839,362	29.73
2	2005	1,225,995	19.81	2	MIDSIZE CAR	1,486,014	24.02
3	2004	833,631	13.47	3	LUXURY CAR	759,971	12.28
4	2007	815,163	13.17	4	COMPACT CAR	706,807	11.43
5	2003	660,975	10.68	5	PICKUP	593,749	9.60
6	2002	385,805	6.23	6	VAN	464,510	7.51
7	2008	250,785	4.05	7	SPORTS CAR	184,297	2.98
8	2001	247,052	3.99	8	FULLSIZE CAR	124,620	2.01
9	2000	183,006	2.96	9	EXCLUDED	27,080	0.44
10	1999	124,512	2.01				

Car Condition			
Rank	**Condition**	**# of Obs.**	**% of Obs.**
1	3	3,622,619	58.54
2	4	1,310,341	21.17
3	2	918,274	14.84
4	1	174,978	2.83
5	5	141,234	2.28
6	0	21,313	0.34

Table 2
Car Condition Levels

The table provides information on how the different car condition codes are constructed.

Grade	0	1	2	3	4	5
Paint & Body	Good for parts only Missing or disconnected mechanical parts Operable, but near the end of its useful life	Sustained major collision damage, but may be drivable May be cost prohibitive to extensively recondition this vehicle by industry standards Repaired or unrepaired collision damage	Dents, scratches and body panels require replacement Parts broken and missing Multiple prior repairs performed of substandard levels Windshield may be damaged	Conventional body and paint work needed Requires parts Sustained cosmetic/light collision damage and repaired to industry standards Minor pitting of glass	Minor conventional body and paint work Small dents that have not broken the paint High-quality conventional repairs of cosmetic/light collision damage	No or minor defects
Interior	Mechanical and body parts may be inoperable, disconnected, damaged or missing	Operability of accessories is doubtful	Signs of excess wear Burns, cuts, tears and non-removable stains	Signs of normal wear and usage Requires repair or replacement of parts	Minimal wear and minor missing or broken parts No odors	Shows no signs of wear
Frame/Unibody			Repaired or unrepaired frame structure or frame damage	No repairs or alterations	No repairs or alterations	No repairs or alterations
Mechanical			Mechanical damage that prohibits operation properly Engine and or transmission in poor condition Operability of accessories is questionable	Mechanically sound Requires maintenance or minor repair of accessories Fluid levels low or require replacement	Sound and operable Fluids may require service	Mechanically sound Accessories are operable Fluid levels full and clean
Tires			Worn or mismatched	Average or better Match by size and style	Identical Good or better condition	Identical Near new condition

Table 3
Auction Characteristics

Summary statistics of auction characteristics in our sample. The table contains information on the most common auction locations, whether auctions were closed to non-franchised dealers, the way purchases were transacted, and the source of the used vehicles.

Auction Open/Closed			Transaction Type			Vehicle Source		
Closed?	**# of Obs.**	**% of Obs.**	**Type**	**# of Obs.**	**% of Obs.**	**Source**	**# of Obs.**	**% of Obs.**
N	4,723,193	76.32	Lane	5,110,836	82.58	Fleet/Lease	4,140,882	66.91
Y	1,465,566	23.68	Upstream	953,435	15.41	Factory	1,741,028	28.13
			Online	124,488	2.01	Dealer	306,849	4.96

Top 10 Auction Locations			
Rank	**Auction Location**	**# of Obs.**	**% of Obs.**
1	Pennsylvania	474,288	7.66
2	Orlando	269,173	4.35
3	Riverside	225,562	3.64
4	Nashville	207,583	3.35
5	Dallas	203,371	3.29
6	Southern California	179,224	2.90
7	Chicago	165,734	2.68
8	New Jersey	157,914	2.55
9	Georgia	155,448	2.51
10	Milwaukee	154,819	2.50

Table 4
Summary Statistics of Select Variables

Variable	Min	Max	Mean	Median	Sd
Run #	1	3,960	185.15	121	227.64
# of Wheel-ins	0	80	0.30	0	0.92
Miles	1	999,991	44,270.38	31,743	36,875.77
Price	0	341,000	13,062.27	12,300	7,560.18
Manuf. CDS	2.5	8,039.70	643.13	520	856.14
# of Same Trim Cars That Day	0	443	8.98	2	19.42
# of Same Trim Cars so Far	0	443	3.39	0	9.44

Table 5
Car Prices and Manufacturer CDS by Car Condition

Condition	Avg. Price	Avg. Manuf. CDS
0	3,743.25	834.06
1	6,753.09	894.28
2	8,681.25	635.18
3	13,111.68	640.04
4	16,340.73	640.99
5	19,085.67	453.94

Table 6
Car Prices and Manufacturer CDS by Mileage Bands

Mileage Band	Avg. Mileage	Avg. Price	Avg. Manuf. CDS
1	4,818.98	19,823.08	614.32
2	10,244.34	17,936.70	649.72
3	13,244.71	17,111.88	625.50
4	15,880.88	16,573.01	609.78
5	18,459.50	16,143.92	603.33
6	20,856.87	15,730.07	616.69
7	23,214.74	15,149.07	627.93
8	25,765.59	14,497.46	638.18
9	28,215.15	13,917.72	701.23
10	30,416.64	13,901.36	691.40
11	33,417.61	14,193.16	644.36
12	37,167.25	14,303.58	591.99
13	41,836.43	13,882.19	570.29
14	47,083.13	13,417.75	553.98
15	53,753.09	11,985.07	578.45
16	62,320.51	10,172.16	616.94
17	73,232.08	8,152.84	678.44
18	87,090.39	6,365.74	719.17
19	106,344.00	4,744.05	747.39
20	152,056.50	3,242.93	783.55

Table 7
Effect of Auto Manufacturers' CDS Spread on Used Car Prices, Baseline Specification

The dependent variable is the (raw or normalized) transacted price of the used cars in the sample. Manuf. CDS refers to the credit-default swap (CDS) spread (in basis points) of the manufacturers of the used cars. Manuf. CDS × Band 2-Band 20 denotes the interactions of Manuf. CDS with a set of dummy variables indicating to which of the 20 mileage bands a car belongs. Other controls not reported in the table include dummies for the auction format the car was sold under, the number of times the car was wheeled through the auction lane, and the number of cars of the same model, trim and model year being sold on the same day in the particular auction location. Columns (1) and (3) also include car condition controls. All regressions include car type-region-week fixed effects. Reported standard errors are clustered on car manufacturers×month, and are reported in parentheses (*** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.)

	(1)	(2)	(3)	(4)
Dependent var:	Price	Normalized price	Price	Normalized price
Manuf. CDS	-0.0679***	-6.07e-06***	-0.00514	-4.80e-06**
	(0.0214)	(1.30e-06)	(0.0340)	(2.30e-06)
Manuf. CDS × Band 2			-0.0419*	-4.19e-08
			(0.0233)	(1.48e-06)
Manuf. CDS × Band 3			-0.0608**	-5.68e-07
			(0.0250)	(1.51e-06)
Manuf. CDS × Band 3			-0.0854***	-2.01e-06
			(0.0296)	(1.71e-06)
Manuf. CDS × Band 4			-0.105***	-2.85e-06*
			(0.0322)	(1.68e-06)
Manuf. CDS × Band 5			-0.119***	-3.44e-06*
			(0.0350)	(1.83e-06)
Manuf. CDS × Band 6			-0.128***	-3.79e-06**
			(0.0338)	(1.60e-06)
Manuf. CDS × Band 7			-0.143***	-4.65e-06**
			(0.0382)	(1.90e-06)
Manuf. CDS × Band 8			-0.149***	-5.42e-06***
			(0.0360)	(1.77e-06)
Manuf. CDS × Band 9			-0.147***	-5.33e-06***
			(0.0381)	(1.56e-06)
Manuf. CDS × Band 10			-0.120***	-4.10e-06***
			(0.0333)	(1.38e-06)
Manuf. CDS × Band 11			-0.132***	-5.40e-06***
			(0.0296)	(1.47e-06)
Manuf. CDS × Band 12			-0.108***	-6.15e-06***
			(0.0324)	(1.96e-06)
Manuf. CDS × Band 13			-0.0811**	-6.93e-06***
			(0.0350)	(2.55e-06)
Manuf. CDS × Band 14			-0.00877	-5.60e-06
			(0.0427)	(3.90e-06)
Manuf. CDS × Band 15			0.0429	-3.29e-06
			(0.0420)	(5.35e-06)
Manuf. CDS × Band 16			0.107**	3.58e-06
			(0.0450)	(6.23e-06)
Manuf. CDS × Band 17			0.151***	1.31e-05*
			(0.0466)	(7.28e-06)
Manuf. CDS × Band 18			0.158***	1.93e-05**
			(0.0482)	(9.48e-06)
Manuf. CDS × Band 19			0.173***	3.30e-05***
			(0.0469)	(1.23e-05)
Constant	10,768***	1.198***	10,720***	1.197***
	(142.5)	(0.00317)	(135.3)	(0.00354)
Observations	6,188,759	6,188,725	6,188,759	6,188,725
R-squared	0.986	0.883	0.986	0.883

Table 8
Effect of Auto Manufacturers' CDS Spread on Used Car Prices, The Warranty Channel

The dependent variable is the transacted price of the used cars in the sample. Manuf. CDS refers to the credit-default swap (CDS) spread (in basis points) of the manufacturers of the used cars. "Car in warranty?" is an indicator variable denoting if a car is still under original factory warranty. This is also interacted with the manufacturer CDS. "Fraction of remaining warranty" is calculated as the minimum fraction between the mileage and age limits; cars out of warranty receive a value of zero. We also use the car condition indicators (0-6) defined in Table 2. Other controls not reported in the table include dummies for the auction format the car was sold under, the number of times the car was wheeled through the auction lane, and the number of cars of the same model, trim and model year being sold on the same day in the particular auction location. All regressions also include car type-region-week fixed effects. Reported standard errors are clustered on car manufacturers×month, and are reported in parentheses (*** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.)

	(1)	(2)	(3)
Dependent var.:	Price	Price	Price
Manuf. CDS	-0.00580	-0.0101	0.463***
	(0.0246)	(0.0322)	(0.0522)
Car in warranty?	1,890***		
	(32.67)		
Car in warranty? × Manuf. CDS	-0.0565**		
	(0.0233)		
Fraction of remaining warranty		4,145***	
		(89.42)	
Fraction of remaining warranty × Manuf. CDS		-0.129*	
		(0.0716)	
Condition 1 × Manuf. CDS			-0.342***
			(0.0358)
Condition 2 × Manuf. CDS			-0.415***
			(0.0437)
Condition 3 × Manuf. CDS			-0.518***
			(0.0510)
Condition 4 × Manuf. CDS			-0.527***
			(0.0542)
Condition 5 × Manuf. CDS			-0.540***
			(0.0690)
Constant	7,414***	7,283***	8,152***
	(124.9)	(132.5)	(99.80)
Observations	6,188,759	6,188,759	6,188,759
R-squared	0.982	0.982	0.979

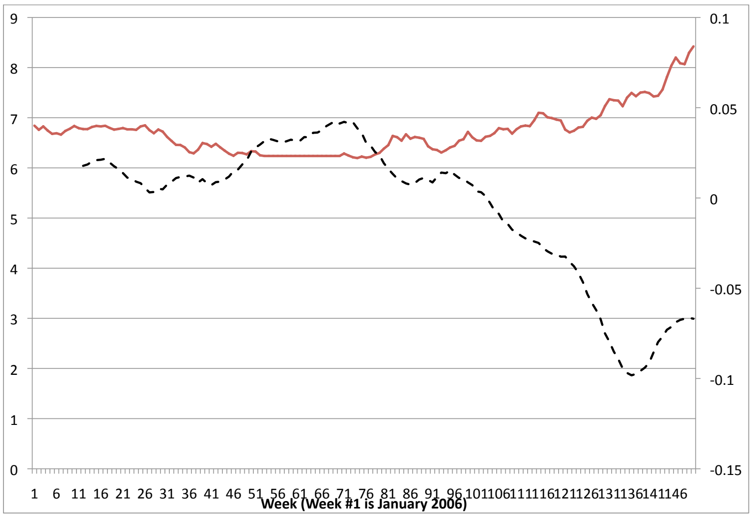
Table 9
Robustness Checks

The dependent variable in the column (1) is the transacted price of the used cars in the sample. "Placebo" Manuf. CDS refers to not the actual manufacturer CDS, but the CDS of an unrelated manufacturer. In columns (2) and (3), the dependent variable is an indicator for whether the buyer is a GM or a Ford dealer, respectively. These regressions use the CDS of the car's manufacturer. Other controls not reported in the table are as in Table 7, and include dummies for the auction format the car was sold under, the number of times the car was wheeled through the auction lane, and the number of cars of the same model, trim and model year being sold on the same day in the particular auction location. All regressions also include car type-region-week fixed effects. Reported standard errors are clustered on car manufacturers×month, and are reported in parentheses (*** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level.)

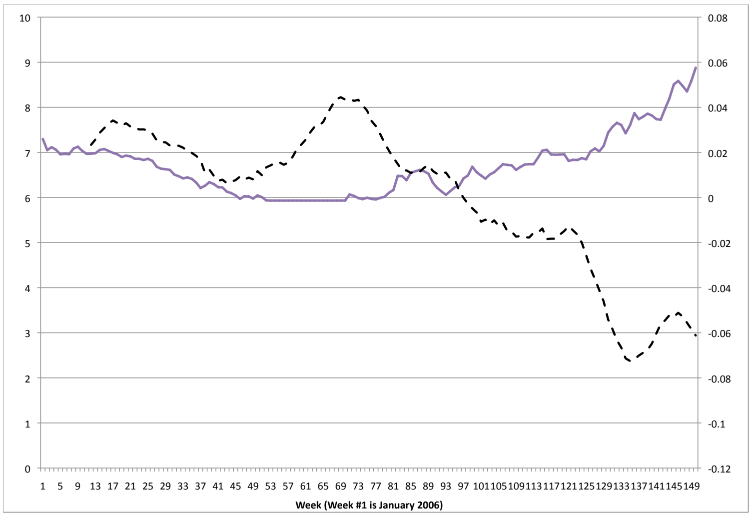
	(1)	(2)	(3)
Dependent var.:	Price	GM dealer buys	Ford dealer buys
"Placebo" Manuf. CDS	0.047		
	(0.0758)		
Manuf. CDS		1.55e-05***	-1.69e-05*
		(4.89e-06)	(1.03e-05)
Constant	15447***	0.299***	0.397***
	(33.10)	(0.00551)	(0.00982)
Observations	6,177,673	1,744,349	1,782,919
R-squared	0.984	0.523	0.513

Figure 1

The panels compare the relative average used car prices and CDS series for Ford (top) and GM (bottom). Each series shows the difference between the appropriate Ford (GM) series and the corresponding series for Honda. The price series are constructed by taking the residual from a regression of cars' auction prices on detailed car type fixed effects, sets of dummies for mileage quantiles, auction location fixed effects, and week-of-year fixed effects. These residuals are averaged by week for every manufacturer, and the difference between Ford's (GM's) and Honda's price series is shown, after smoothing using a 12-week moving average, in the figure. The CDS series are computed by taking the car-weighted average CDS value for each manufacturer and subtracting Honda's series from Ford's (GM's). The log of this difference is shown in the figure to make visualization easier.



(a) Ford



(b) GM

Figure 2
Illustrative Figures of Used Car Auctions

(a) Auction Site

(b) Inside an Auction

(c) The Auction Online

Figure 3
Auto Manufacturer CDS Spreads

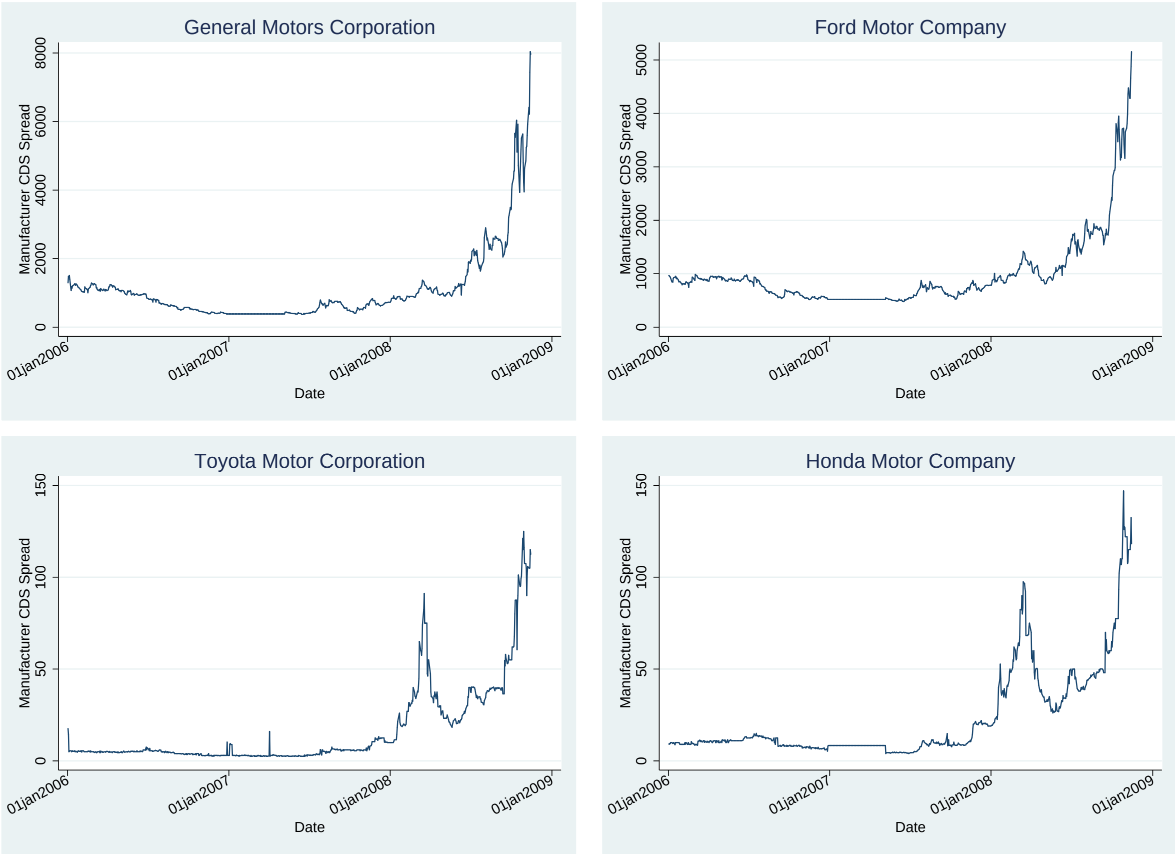


Figure 4
Plot of Mileage Interaction Coefficients from Column (3) of Table 7