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Essays on Bankruptcy-Induced Exits and Market Outcomes

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Doctor of Philosophy

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Essays on Bankruptcy-Induced Exits and Market Outcomes

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B.S., Galatasaray University, 2004

M.S., Koç University, 2006

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An abstract of

A dissertation submitted to the Faculty of the

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Abstract

Essays on Bankruptcy-Induced Exits and Market Outcomes

By Ömer Cem Öztürk

The objective of this dissertation is to empirically investigate the effect of bankruptcy-induced exits on product market competition and consumer demand. Specifically, this study looks at the impact of Chrysler LLC's dealer closings as part of its Chapter 11 bankruptcy process in 2009.

The first essay is descriptive, where the objective is to characterize "how" consumer demand and incumbent dealers react to Chrysler LLC dealer terminations. The analysis is conducted using a limited information-based bias-corrected matching estimator. My findings highlight several striking patterns on the consumer and firm side reactions to local market Chrysler LLC dealer terminations. Specifically, I describe how these reactions vary by the brand identity of the terminated dealership, by incumbent brand and by product category.

The second essay focuses on the consumer side and estimates a dynamic structural demand model to run counterfactual simulations in order to better understand the implications of Chapter 11 bankruptcy induced exits. Results of the counterfactual simulations suggest that bankruptcy-induced dealer closings significantly affect what, when and where consumers buy. Accordingly, the insights generated in this essay have appeal to marketing academicians, automobile manufacturers, automobile dealers, and regulators alike.

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CHAPTER 1

Overview

The recent global financial crisis and the resulting economic meltdown culminated in thousands of firms spanning diverse industries filing for bankruptcies. In the United States, automobile giants General Motors (GM) and Chrysler LLC both filed for Chapter 11 bankruptcy protection and sought capital infusion from the Federal government. The two firms in turn were forced to streamline their operations, change their debt financing, renegotiate their union contracts and drastically reduce their dealer distribution network. While General Motors chose to terminate 1,454 (26 percent) dealer contracts after the current contracts expire in 2010, Chrysler LLC immediately terminated 789 (25 percent) of its 3,181 dealerships. Distribution network changes of such magnitude are unprecedented since state franchise laws limit manufacturers from terminating their incumbent dealer sites. Because these developments are so recent, no academic research currently exists which formally examines the impact of these dealer network changes.

My dissertation comprises two essays. Together, they investigate the impact of the Chrysler LLC dealer terminations on consumer demand and inter-firm competition. In doing so, they build on the emerging literature in economics and finance investigating the role of firm bankruptcies on product market competition. The extant literature has so far focused on firm side decision variables that are more relevant to regulators and corporate finance. The impact of bankruptcies on consumer demand or firm side decisions like pricing, assortment planning and inventory management have received little to no attention. My dissertation fills this research gap using a rich new database of monthly dealer-level panel data that include pricing, assortment and inventory variables between 2008 and 2010. The data are at the individual car level and include the census of new car dealerships across 4,500 cities in the U.S.

The first essay is descriptive, where the objective is to characterize "how" consumer demand and incumbent dealers react to Chrysler LLC dealer terminations. The analysis is conducted using a limited information-based bias-corrected matching estimator (Abadie and Imbens 2002). This estimator has been widely used in the program evaluation literature in economics to make causal inferences without imposing too much structure. My findings highlight several striking patterns on the consumer and firm side reactions to local market Chrysler LLC dealer terminations. Specifically, I describe how these reactions vary by the brand identity of the terminated dealership, by incumbent brand and by product category. The current descriptive analyses identify evidence of a short-run effect of bankruptcies on consumer demand and product market competition.

In Essay 2, I add more structure to the empirical analysis conducted in Essay 1. Herein, I focus on the consumer side and estimate a dynamic structural demand model to run counterfactual simulations in order to better understand the implications of Chapter 11 bankruptcy induced exits. I estimate a structural demand system similar to Gowrisankaran and Rysman (2009) while accounting for forward-looking consumer considerations, endogeneity of prices, endogenous repeat purchases and product differentiation. Like Gowrisankaran and Rysman (2009), consumers perceive that the evolution of the value of their new car purchase follows a simple one-dimensional Markov process and they rely on a reduced-form approximation of the supply side evolution to make predictions about the value of their future purchases. The novel feature of my model is the incorporation of local market level online search data with dealer level aggregate sales data, to capture spatial heterogeneity in consumer preferences. In addition, my model extends previous studies by taking into account deterministic product depreciation. The estimated model is used to compare the predicted adoption by consumers under different distribution strategies: no termination vs. termination as observed in the data. More precisely, I predict consumer choices under different regimes and report the differences in outcomes at the manufacturer and dealer levels. The results indicate that bankruptcy-induced distribution changes have substantial impact on manufacturer and dealer market shares due to their impact on what, when, and where consumers buy.

CHAPTER 2

Essay 1: Assessing Incumbent Auto Dealers' Reactions to Chrysler LLC's Bankruptcy-Induced Dealer Network Pruning

2.1 Introduction

In June 2009, two of America's three auto manufacturers (GM and Chrysler LLC) became the first U.S. auto manufacturers in history to file for Chapter 11 bankruptcy. The move gave Chrysler LLC and GM the freedom to prune their dealer network under bankruptcy court protection. Chrysler LLC cut 789 dealers immediately (25 percent of its dealer network), and in the process increased the percentage of dealers selling all three of its brands (i.e. Dodge, Chrysler and Jeep) to 84 percent from 62 percent. GM announced plans to eliminate more than 1,300 dealers by October 2010.[1] Such historic changes were designed to let the "new GM" and the "new Chrysler" emerge from bankruptcy with fewer assets and liabilities.

[1] Interested readers are referred to Canis and Platzer (2009) for a breakdown by state.

Distribution channel changes of this magnitude are unprecedented in the U.S. auto industry because federal and state franchise laws make it very difficult for automobile manufacturers to terminate dealerships or reconfigure locations of existing dealerships (Lafontaine and Morton 2010). However, under bankruptcy protection these constraints were lifted for the two financially distressed auto manufacturers. Although these dealer terminations have been the topic of significant debate in the popular press and in public policy circles, and despite their enormous economic significance, there does not seem to be any scholarly research empirically examining the impact of these dealer terminations on incumbent dealers and automobile manufacturers. This is the central research objective of this study.

In this article, I study how incumbent auto dealers react to a bankruptcy-induced exit of a Chrysler LLC dealership in their local market and the consequences of these reactions for the dealers' outcomes (unit sales). My specific research objectives are: (1) to quantify how incumbents change their pricing, inventory, and product assortment in response to this bankruptcy-induced exit, and how their sales are affected by the exit; (2) to quantify how incumbent dealer reactions and sales outcomes vary by auto franchise (e.g. Honda vs. Toyota dealers), and product categories (e.g. sedan vs. SUV), and (3) to quantify how incumbent dealer reactions and sales outcomes vary by brand affiliation of the exited dealership (Dodge, Chrysler or Jeep).

This article builds on and contributes to the rich literature in marketing that studies competitive reactions. Herein, examples of how incumbents react to entry or the threat of entry abound (see Hauser and Wernerfelt 1988; Gatignon et al. 1989; Shankar 1997; Tyagi 1999; Basker 2005; Singh et al. 2006; Goolsbee and Syverson 2008; Gielens et al. 2008; Basker and Noel 2009; Olivares and Cachon 2009; Ailawadi et al. 2010). However, there does not seem to exist any systematic research examining how incumbents respond with their marketing mix to the exit of a competitor.[2] This study addresses this research gap.

However, several countervailing demand and supply side motivations make predicting and quantifying the incumbent dealers' marketing mix reaction to the exit and, in particular, bankruptcy-induced exit, challenging. I highlight some of these below.

[2]There are few structural econometric studies investigating the incumbents' reactions to entry. However, these reactions have been limited to incumbents' stay/exit decisions. These studies do not focus on how incumbents alter their marketing mix based on the exit of a competitive firm.

Conceptually, when a competing Chrysler LLC dealer exits a market, an incumbent dealer (either a surviving Chrysler LLC dealer or a dealer of a competing auto manufacturer) in that market can react by adjusting one or more elements of its marketing mix elements (price, inventory and assortment). These adjustments may vary by product category that the incumbent carries (sedan, hatchback, SUV, etc.) and by the characteristics of the exiting dealer (proximity to the exiting dealer and brands and product categories carried by the exiting dealer). For each marketing mix variable in each category, an incumbent can react in three possible ways: do nothing, significantly decrease the variable, or significantly increase the variable.

Within a product category, tempered competition may lead incumbents to increase prices. This is counter opposite to the "retaliatory" reaction of incumbents to new entry (Ramaswamy et al. 1994; Shankar 1999; Steenkamp et al. 2005). The prospect of demand spillover (i.e. customers who would otherwise have purchased a car at the exited Chrysler LLC dealer) may also motivate incumbent dealers to sacrifice unit margins and make up the lost margins with higher sales volume. Along the same lines, tempered competition reduces incumbents' stock-out costs, since consumers now have fewer alternatives for where and what to purchase (Olivares and Cachon 2009). Therefore, a Chrysler LLC dealer exit may induce incumbents to decrease their inventory and product assortment. However, the prospect of demand spillover may also induce incumbents to increase their inventory and product assortment so as to attract and sell to a larger pool of prospective buyers.

Might these competitive reactions be different for incumbent dealers of competing manufacturers vs. surviving Chrysler LLC dealers? Why? As previously mentioned, the vertical contracting arrangements between dealers and auto manufacturers are tightly regulated by federal and state franchise laws (Lafontaine and Morton 2010). These laws make it very difficult for manufacturers to shut down dealerships and almost guarantee dealership profitability and survival, even at the expense of manufacturer profits.[3] Only under Chapter 11 protection was the financially distressed Chrysler LLC able to terminate dealerships, many of which are generating significant profits for the franchisee owning the dealership.

Chrysler LLC faces cost shocks inherent to operating under court protection such as the

[3] GM spent $1 billion to terminate more than 2,000 Oldsmobile franchisees (Surowiecki 2006).

ability to renege and renegotiate contracts to lower its marginal costs. Lower marginal costs can lead surviving Chrysler LLC dealerships to reduce their price or maintain the same pre-pruning price and net higher unit margins post-pruning. If these cost savings are large and passed through to the surviving Chrysler LLC dealerships, one might expect greater downward price pressure on dealers of competing manufacturers.

However, on becoming cash constrained, the highly leveraged Chrysler LLC may also charge higher prices to the surviving Chrysler LLC dealers after filing for bankruptcy than its non liquidity constrained rival firms (Chevalier and Scharfstein 1996). This would suggest that surviving Chrysler LLC dealers may charge higher prices post dealer network pruning.

Competing auto manufacturers not under bankruptcy court protection are still subject to federal and state franchise laws and not permitted to close/reconfigure their existing dealerships. This leaves them little choice but to respond with their marketing mix. If the surviving Chrysler LLC dealers react to the exit by raising prices, one may expect that dealers of rival manufacturers might also increase their prices. However, rival firms may not increase their prices if the Chapter 11 bankruptcy protection filing of the distressed manufacturer presents a unique opportunity for predation. If predation is feasible, then rivals have an incentive to cut their own prices and thus reduce the profits of their local surviving Chrysler LLC competitors. Therefore, if predation occurs, we would expect to see prices of non-Chrysler LLC dealers drop following the exit of a Chrysler LLC dealership.

If the degree of demand spillover from terminated Chrysler LLC dealer is higher for the surviving Chrysler LLC dealers than dealers of competing manufacturers, then surviving Chrysler LLC dealers are likely to exhibit reactions of greater magnitude than competing dealers. If the overall elasticity of substitution between Chrysler LLC product lines and non-Chrysler LLC product lines is small, then one might expect competing dealers not to exhibit significant reactions to Chrysler LLC dealer network pruning.

Being a durable good, the consumption stream that automobiles provide frequently depends on product warranties, the availability of spare parts, maintenance, and upgrades. For example, a prospective new car buyer will factor in 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 in the near future. If a car manufacturer were to go bankrupt, it is not obligated to honor the warranties or provide parts and services in the future, reducing the consumption of the durable goods owner.

By filing for Chapter 11 protection, the distressed Chrysler LLC may have effectively increased consumer uncertainty towards its product line, resulting in eroding its own brand equity (Hortaçsu et al. 2011). These demand shocks result in reduced demand for Chrysler LLC products, as advanced in Opler and Titman (1994). These negative demand shocks do not occur if the exit were not bankruptcy induced, but rather was a voluntary exit by the local Chrysler LLC dealership.

Negative demand shocks would imply that despite tempered intra-firm competition, surviving Chrysler LLC dealerships will have to drop prices significantly to sustain pre-pruning sales levels and eroding consumer confidence in their products. This would also imply that dealers of competing manufacturers have higher market power and would react by setting higher prices post bankruptcy-induced Chrysler LLC dealership exit.

Last but not least, in this setting, Chrysler LLC's dealers sell cars belonging to all three Chrysler LLC brands (Chrysler, Dodge and Jeep) or a subset of them. These brands span different product categories like sedans, hatchbacks, SUVs, etc. Brand affiliations and product portfolios of the terminated dealers are different across geographic markets. Whether incumbents' reactions to a Chrysler LLC dealer exit vary with the brand affiliation of the terminated Chrysler LLC dealer or by product category that the terminated dealer carries remains an open empirical question.

The net effect of these aforementioned divergent demand and supply side motivations on incumbent reactions remains an unanswered research question and the key empirical contribution of this study.

The current study also contributes to the sparse empirical literature on the economics of bankruptcies (Borenstein and Rose 1995, 2003; Chevalier 1995; Chevalier and Scharfstein 1996; Ciliberto and Schenone 2010).[4] Several features of our study make it different relative

[4]Hortaçsu et al. (2011) show that the financial distress of the firm can impact product market competition even before the distressed firm files for bankruptcy protection. For example, auto owners rely on warranties to cover malfunctions, car parts when the car breaks down, and access to a local dealer to service the car. In the U.S.,

to previous studies in this research stream. Previous studies shed valuable light on the U.S. supermarket (Chevalier 1995) and the U.S. airline industries (Borenstein and Rose 1995, 2003; Ciliberto and Schenone 2010). The current study instead examines the U.S. automobile industry and the industry's first Chapter 11 bankruptcy filing. In the airline industry, the airline carrier may chose to exit a market altogether or reduce the capacity to and from a geographic market at any time. Rivals can respond by pruning their own retail network (Ciliberto and Schenone 2010). In the automobile industry, state franchise laws prevent rival manufacturers from pruning their own dealer network.

Instead of comparing reactions pre- and post-bankruptcy filing (Ciliberto and Schenone 2010) or during bankruptcy protection (Borenstein and Rose 1995), the current study focuses entirely on the period after bankruptcy-induced reorganization.

While previous studies have examined outcomes more relevant to finance and economics, I examine more marketing pertinent decisions like price, retail assortment and retail inventory in the period after dealer terminations. Extant studies have either not allowed the reactions to be different across the bankrupt firm and its rivals (Borenstein and Rose 1995, 2003; Chevalier 1995) or limited them to be different across the distressed firm and its rivals but not geographically varying. In contrast, my data and empirical strategy allow incumbent reactions to vary across firms and markets.

To conduct this research, I compile a rich new database that contains dealer-specific monthly information for the census of all auto dealers in the U.S. These data cover two years (2008 and 2009) and include time periods both before and after Chrysler LLC's Chapter 11 induced dealer terminations. The data contain nine brands (Chevrolet, Ford, Chrysler, Jeep, Dodge, Mazda, Toyota, Nissan and Honda) spanning eight product categories (convertible, coupe, hatchback, sedan, SUV, truck, van and wagon).

My empirical strategy is closest in spirit to Ailawadi et al. (2010), who examine the effect of Walmart entry on incumbent retailers' marketing mix reactions and sales outcome. Varia-

these services are frequently vertically integrated into the manufacturer. Their study shows that the belief that a financially distressed car manufacturer may not honor the warranties or provide parts and services in the future can reduce consumers' consumption of the durable goods from that firm even before the manufacturer files for bankruptcy. That is, the mere expectation of probable bankruptcy may reduce the expected value of durable goods to a forward-looking consumer.

tion in the location of Chrysler LLC dealerships that were terminated under bankruptcy court protection, when combined with my new dealer-specific database, affords me the opportunity to identify "similar" markets both with and without exits. This enables me to perform a before-and-after with control group analyses using a limited information-based bias-corrected matching estimator, and thereby to draw causal inferences on the impact of the aforementioned bankruptcy-induced exits.

The findings suggest that incumbent dealers react by changing prices (both upward and downward), followed by changing their inventory (both increasing and reducing it) and lastly assortment (some reduce and some increase their product portfolios). Surviving dealerships of Chrysler LLC uniformly increase prices, but show the same mixed reactions as rival manufacturers' dealerships when it comes to inventory and assortment.

I also find that the brand identity (Dodge, Chrysler or Jeep) of the terminated Chrysler LLC dealer matters. When Dodge dealerships shut down, American brand dealerships raise their prices, while their Japanese counterparts drop prices. However, when a Jeep dealership gets terminated, the reactions are just the opposite.

Another key finding will interest policy makers. At the outset, Chrysler LLC argued that one of the driving reasons it needed to declare bankruptcy was that its prices were in a downward spiral as competing dealerships within its own network cannibalized each other in a race to the bottom. I show that by seeking Chapter 11 protection, Chrysler LLC's ability to prune its dealership under the terms of bankruptcy did, indeed, trigger a rise in its pricing power post-pruning. This lends empirical support for Chrysler LLC's pre-bankruptcy claim of excess distribution.

The remainder of the paper is organized as follows. First, I review the U.S. automobile industry and related academic literature and highlight key structural changes the industry has undergone as a result of the recent economic crisis. Second, I describe my novel database. Third, I discuss my identification strategy and the empirical specification. Fourth, I present the results from the empirical analysis. Finally, the last section concludes.

2.2 U.S. Automobile Industry and Financial Crisis

The automotive industry is an important pillar of the U.S. economy. The "Detroit Three" – i.e., General Motors, Ford and Chrysler – alone employ 880,000 workers (6.6 percent of the U.S. manufacturing workforce) and contribute approximately 3.6 percent, or $500 billion, to the total Gross Domestic Product (GDP) output. Automobiles account for about five percent of consumption in the U.S. and are the non-financial asset most commonly held by households (Hortaçsu et al. 2011). They represented roughly three percent of U.S. household wealth in 2007 (Bucks et al. 2009). Generating $758 billion in revenues in 2007, the auto retail industry became the largest retail sector in the U.S., exceeded the retail sales of other large retail industry sectors, including general merchandise stores, food and beverage stores, and gasoline stations (see Figure 1). Combined U.S. auto dealers (new and used car dealerships) accounted for 7.9 percent of total retail employment, directly providing jobs for an estimated 1.2 million American workers in 2008, based on preliminary employment statistics from the U.S. Department of Labor.[5]

Given its economic significance and rich institutional features, the automobile industry has had natural appeal to marketing and management scholars. Academic research examining this industry has generated rich insights around pricing (Boyle and Hogarty 1975; Bresnahan 1981; Berry et al. 1995; Sudhir 2001), consumer-directed price promotions (Pauwels et al. 2004; Bruce et al. 2006), trade promotions (Bruce et al. 2005), buyer-supplier links (Martin et al. 1995), channel pass-through (Busse et al. 2006), information search (Punj and Staelin 1983), leasing vs. selling (Desai and Purohit 1998, 1999; Bhaskaran and Gilbert 2009), new vs. used car competition (Purohit 1992), consumer adoption decisions (Schiraldi 2011), dealer-consumer negotiations (Desai and Purohit 2004), product obsolescence (Levinthal and Purohit 1989), hybrid car adoption (Huang 2010; Gallagher and Muehlegger 2011), etc.

However, in the past decade, the Detroit Three have seen their share of the domestic market drop from 64.5 percent in 2001 to 47.5 percent in 2008. The decline in U.S. motor vehicle sales

[5]The employment statistics are based on preliminary annual data for 2008 reported by the U.S. Department of Labor, Bureau of Labor Statistics, Quarterly Census of Employment and Wages (QCEW) program. It includes all employees who work at automobile dealers included in North American Industry Classification System (NAICS) category 4411 (this category covers new and used car dealers).

accelerated in late 2008, with monthly sales running more than 30 percent lower than the same month the year before. Americans bought 13.2 million cars and light trucks in 2008, below the 16.1 million units sold in 2007, and well below the peak of the 17.8 million sold in 2000. For the full year, the Detroit Three were the hardest hit, with 2008 sales falling by 30.3 percent, 22.7 percent and 20.3 percent for Chrysler LLC, GM, and Ford, respectively.[6] Until 2009, the U.S. was the world's largest car market but a recession led decline in U.S. sales and a parallel surge in Chinese purchases made China the world's largest single auto market. In 2008 alone, the industry shed 50 percent of its sales volume and slashed 400,000 jobs.

Despite declining sales, union contracts severely restricted manufacturers' ability to shut down production facilities (SIGTARP 2010) and state franchise laws curtailed them from terminating their contractual obligations with their downstream channel dealer distribution network (Lafontaine and Morton 2010). The confluence of all these factors was so catastrophic that at the end of 2008, General Motors and Chrysler LLC were unable to secure the day-to-day funding needed to remain in business.

Legislation was introduced in the 110th Congress to implement a federal loan program to prevent one or more of the Detroit Three from falling into bankruptcy, but no bills were approved. Congress in December 2008 left the decision whether and how to assist the Detroit Three companies to the Bush Administration. On December 19, 2008, President George W. Bush announced a plan to lend $17.4 billion from the Troubled Asset Relief Program (TARP) to General Motors and Chrysler LLC to prevent any near-term bankruptcy and to help them restructure as more viable and competitive companies over the longer term. After accepting loans under the terms of these agreements, General Motors and Chrysler LLC presented forward-looking business plans, as required in the agreements, on February 17, 2009.

The plans indicated how they could become financially viable and pay back federal loans. Both companies indicated that they would require additional federal financial support to achieve long-term viability. However, the proposed measures by the two firms were deemed "not viable as currently structured" by the U.S. Treasury Department. General Motors and Chrysler LLC were advised to use the terms of bankruptcy to quickly eliminate large numbers of cost driving

[6] Ward's, Motor Vehicle Facts and Figures, 2009.

dealers from their dealer network, an action that the two manufacturers could not otherwise pursue given state level dealer leaning franchise laws (see Figure 2 for the timeline of events).

As per recommendations from the U.S. Treasury Department, both Chrysler LLC and General Motors filed for Chapter 11 bankruptcy protection on April 30, 2009 and June 1, 2009 respectively. The move gave Chrysler LLC the freedom to immediately terminate 789 (or 25 percent) of its 3,181 dealerships.

The "new Chrysler" and "new GM" have emerged from bankruptcy as significantly smaller companies. The "new Chrysler" is now controlled by the Italian car maker Fiat, while the current majority owner of the "new GM" is the U.S. government. The "old GM," which in 2008 operated 47 assembly, powertrain, and stamping facilities, is slated to operate 34 plants by the end of 2010 and 33 by 2012. The number of hourly employees will have declined from 78,000 on December 31, 2007, to 62,200 at the end of 2008, and to 40,000 in 2010. By way of contrast, GM had 304,000 hourly workers in 1991. GM also discontinued one brand (Pontiac) and is to sell Hummer, Saab, and Saturn, and some percentage of its GM Europe operations, Opel and Vauxhall. The new Chrysler reduced its number of production facilities from 25 to 17 as part of its restructuring. The company employed 45,000 hourly U.S. employees in January 2008 and 27,000 in February 2009. For the first time, GM and Chrysler are not owned by private investors. Rather, the United Auto Workers (UAW)'s[7] retiree health trust, the U.S. Treasury Department, and the Canadian government have taken ownership stakes in both companies. These seismic shifts in the market offer scholars unique and exciting opportunities for research inquiry.

2.3 Data

I compiled a rich new database that combined information across several different databases. One database contains city-brand-category-specific monthly retail information. These data were provided by a large market research firm that prefers to remain anonymous. In this

[7]The International Union, United Automobile, Aerospace and Agricultural Implement Workers of America is one of the largest and most diverse unions in North America, with members in virtually every sector of the economy.

database, for the years 2008 through 2009, I have the posted retail price for each automobile that the dealer holds in inventory in a given month. Here, each automobile is uniquely identified by its vehicle information number (VIN). The data span nine brands (Chevrolet, Ford, Chrysler, Jeep, Dodge, Mazda, Toyota, Nissan and Honda), eight product categories (convertible, coupe, hatchback, sedan, SUV, truck, van and wagon), and 16,637 dealerships spread over 4,513 cities in the U.S. I matched these data with the 789 Chrysler LLC terminated dealers spread across 684 cities. I was successful in matching 671 of the 789 terminated dealers. To ensure that my results are not biased, I do not include markets where I was unable to match all the terminated dealers in that market.

Given the central research question, dealer specific data are aggregated to generate city-month-brand-category level measures. Price is the average retail price, averaged across all automobiles for a specific brand-category combination carried by dealers in a city in a given month. Similarly, inventory is the average inventory carried by dealers of a specific brand-category combination in a focal city in a given month. Assortment size is measured as the average number of distinct auto models carried by a dealer for a specific brand-category combination in a city in a given month. Sales are measured as the average number of units sold by a dealer for a specific brand-category combination in a city in a given month.

Tables 2 through 5 characterize the variation in the data that I exploit to estimate the treatment effect. Recall that the terminated Chrysler LLC dealerships can either be Chrysler, Dodge, or Jeep dealerships. As seen in Table 2, there are 194 unique category-city-month observations where a Chrysler LLC dealership was terminated. For these 194 observations, I have 36,822 observations that may serve as potential matches that span our nine brands (including Chrysler) and eight product categories. These 36,822 observations belong to other city-month pairs where a Chrysler brand affiliated dealership did not get terminated. Along the same lines, there exist 412 (786) Dodge (Jeep) treatment condition observations for which we have 36,604 (36,230) potential matching candidates.

For each terminated brand (row elements), in each corresponding column, I report the number of treatment observations (and non-treated), the mean and the standard deviation for the four focal variables of interest (grouped columns). I report separately this aforementioned information for the associated treatment and non-treated samples. The descriptive statistics show that means for the treatment and non-treated are quite similar (preliminary evidence in support of our treatment-exogeneity assumption). However, the standard deviations are quite different. This is as one might expect, as there are far fewer treatment observations than non-treatment observations.

It is also likely that some of the 36,822 matching pool candidates for Chrysler could experience the termination of either a Dodge or Jeep dealership. Including these observations as matching candidates will clearly bias the recovered treatment effect estimate. Hence, I limit the universe of matching candidates to observations coming from cities with no Chrysler LLC terminations. To ensure that dealers in these markets were not reacting to anticipated General Motors dealer closings, I limit the universe of matching candidates and treatment markets to cities with no impending General Motor dealer consolidations. From this candidate pool, the bias-corrected matching estimator will identify a subset of matches (conditioned on observable covariates, described later).

In Table 3, I highlight the sample size of the treatment and potential non-treatment matching samples across product categories by focal outcome variable and terminated Chrysler LLC brand. Note that each product category can include one or more of the nine brands. For example, in the data there are eight city-month observations associated with cities with convertible auto dealers where the associated city experienced a Chrysler brand termination. For these eight observations, I have potentially 1,787 city-month observations in the universe of matching candidates.

For the same treatment condition (i.e. Chrysler termination), the number of treatment and non-treatment observations are much higher for non-convertible cars because the distribution network of other product categories is much larger than the network of dealers selling convertibles. It is also worth noting that for the same outcome variable, the potential matching candidate pool will be the same across the three treatment conditions (three terminating brands) for a given product category, but will vary across product categories. This is because the universe of matching candidates does not include observations from markets where any Chrysler LLC brand was terminated or a General Motors dealership is slated to be terminated.

Next, in order to estimate the treatment effect by brand, the matching estimator will identify a set of suitable matches from the universal matching candidate pool, where the non-treated candidates are affiliated with the focal brand. As seen in Table 4, there exist 32 city-month observations affiliated with the Chevrolet brand where the underlying city experienced the termination of a Chrysler brand affiliated dealership and no Dodge or Jeep dealerships were terminated in that market. Out of the universe of matching candidates, there are 9,377 city-month Chevrolet brand observations that span some subset of the eight product categories where Chevrolet has a presence.

Note that since the universe of matching candidates is the same for all three brands associated with Chrysler LLC dealer terminations, the same 9,377 observations will also serve as matching candidates to estimate the treatment effect of Chevrolet incumbent dealers when instead of the Chrysler, either the Dodge or Jeep dealerships were terminated. However, the sample of treatment observations will differ across the terminated brands. This is because the Dodge terminating city-month treatment observations are different from the Chrysler terminating treatment observations.[8] Note also there are no treatment markets with Honda and Mazda dealerships where a Chrysler dealer was terminated. Hence, conditioned on the observable covariates, our recovered treatment effects for Mazda and Honda should potentially be smaller that the treatment effects of other incumbent brands.

I collected data on the observable covariates from different sources. I obtained the weekly regular retail gas price data from the U.S. Energy Information Administration website. Then I took the average across weeks to calculate a monthly measure of gas price. I collected data containing employment, the number of households with no vehicle, population, median income, and population density using a web-based application. The data provided by this web-based application are from Easy Analytic Software Inc., Mediamark Research Inc., and Simmons Study of Media Markets and are derived from government and other sources. Here, too, there is a rich source of cross-sectional and temporal variation (see Table 5).

Taken together, the descriptive statistics tables reveal rich spatio-temporal variations in market contact across incumbent brands and the brand affiliation of the terminated dealership. It

[8] A treatment observation can only experience one of the three treatments.

is this rich source of variation that will allow me to pin down both our average treatment effect (by terminated dealership brand) and variation across incumbent brands conditional on the same terminated brand dealership. The recovered brand-specific treatment effects can offer rich insights on the inter-brand market structure, be it in the marketing mix or changes in unit demand.

2.4 Empirical Approach and Identification Strategy

My causal inference strategy is analogous to program evaluation studies in economics concerned with the effects of being or not being in a particular program (Rubin 1973; Rosenbaum and Rubin 1985; Heckman, Ichimura, Smith and Todd 1998). The program/treatment in this setting is a bankruptcy-induced Chrysler LLC dealership termination within a local market (city-state pair) and the causal effect I seek to infer is its impact on incumbent dealers' marketing mix and sales.

As is typical with the microeconometric evaluation studies, each economic unit of analysis (a unique city-state pair in this study) is in one of two states of the world, i.e. either it has seen a Chrysler LLC dealer network termination (treated) or it has not (non-treated). Several econometric approaches have been developed for estimating the average effect of receiving or not receiving a treatment under the assumption that the treatment satisfies some form of exogeneity.[9]

The exogeneity assumption implies that a market's receipt of the treatment is independent of the potential outcomes with and without treatment if certain observable covariates are held constant. In my empirical setting, this implies that there exist cities where, conditioned on a set of city-specific observable covariates, the likelihood of them seeing a Chrysler LLC termination or not is independent of the potential outcomes. This assumption affords me the ability to attribute any systematic (for example, average or distributional) differences in outcomes between

[9]The exogeneity assumption is referred to as unconfoundedness (Rosenbaum and Rubin 1983), selection on observables (Barnow et al. 1980; Fitzgerald et al. 1998), or conditional independence (Lechner 1999). In the terminology of Rosenbaum and Rubin (1983), the treatment assignment is "strictly ignorable" given a set of certain observable characteristics X.

treated cities and non-treated cities with the same set of observable covariates as the treatment effect, i.e. the effect of the Chrysler LLC dealer closings.

The estimation techniques can vary from (i) methods based on estimating the unknown regression functions of the outcome on the covariates (Hahn 1998; Heckman, Ichimura and Todd 1998; Imbens et al. 2003); (ii) matching on covariates (Rosenbaum 2002; Abadie and Imbens 2002); (iii) methods based on the propensity score, including blocking (Rosenbaum and Rubin 1984) and weighting (Hirano et al. 2003); (iv) combinations of these approaches, for example, weighting and regression (Robins and Rotnitzky 1995) or matching and regression (Abadie and Imbens 2002); and (v) Bayesian methods.

In this study I employ an Abadie and Imbens (2002) style bias-corrected matching estimator.[10] The Abadie and Imbens (2002) estimator is a bias-corrected matching estimator. As stated previously, the matching is done on observable market-specific covariates. Like previous studies, this study also suffers from the difficulty that one can never be completely certain that the bankruptcy-induced Chrysler LLC terminations caused the change in incumbents reactions. It may be that a common factor leads Chrysler LLC to terminate select dealers in a treatment market and also changes the surviving incumbent dealers' marketing mix reactions post Chrysler LLC dealer termination. Unfortunately, this difficulty is also present in this paper, although steps have been taken to try to show that the recovered incumbent reactions are caused by the Chrysler LLC terminations. Specifically, my use of local market data in this study also ameliorates the reverse causality problem.

I show that marketing mix reactions of incumbent dealers of the same manufacturer differ across geographic markets, depending on the characteristics of the local market. It is difficult to imagine a cost or demand shock that would tend to cause dealer terminations and would cause incumbent dealers' reactions to rise in some markets and fall in others.[11]

[10]Haviland et al. (2007) combine group-based trajectory modeling with propensity score-based matching to control bias from other covariates besides the baseline measures of the outcome variable. As a robustness check, I also calculated the average treatment effects combining the group-based trajectory modeling part of their approach with the Abadie and Imbens (2002) approach. The trajectory modeling step requires me to have matched pre-treatment longitudinal data both for the treated and non-treated groups. For the cities that meet this criterion, the results across the two approaches are very similar. Hence, I will limit the discussions going forward to the Abadie and Imbens approach only. The results after including the trajectory modeling step can also be appended if deemed necessary.

[11]The problem of unobservables components is not peculiar to matching estimators. Alternate empirical methods

Furthermore, in my empirical analysis I allow the matching to be time varying, while allowing the matching candidates to be matched more than once;[12] hence implicitly I allow the treatment effect to vary over time for the same economic unit. The bias introduced via the multidimensional matching procedure is allayed using a bias-corrected procedure that adjusts for the differences in covariates between the treated market and its matches. I briefly outline the econometric model below, and I will begin with a general description of the estimation approach and later describe the actual estimator I take to the data.

The economic unit (p) in the current study is a city (i)-month (t) pair.[13] Let $Y_p(1)$ and $Y_p(0)$ denote the outcome when p is exposed to a Chrysler dealer termination ($W_p = 1$) or when it is not ($W_p = 0$). If both $Y_p(1)$ and $Y_p(0)$ were observed, then the effect of the treatment on p is nothing but $Y_p(1) - Y_p(0)$.[14] However, only one of the two outcomes is observed. Hence, we need to estimate the non-treated outcome $Y_p(0)$ for observation p with covariates X_p, which was exposed to the treatment. The difference between the treated outcome $Y_p(1)$ and the estimated non-treated outcome $\hat{Y}_p(0)$ is the treatment effect for unit p. The basic idea of the estimator is to impute the missing outcome for p by finding other economic units in the data whose covariates are similar to p but which were exposed to the other treatment. It is the process of "matching" similar economic units who received the opposite treatment that causes these estimators to be known as "matching estimators."

Let $d_M(p)$ be the distance from the covariates for unit p, X_p, to the Mth nearest match with the opposite treatment. Allowing for the possibility of ties, this is the distance such that strictly fewer than M units are closer to unit p than $d_M(p)$, and at least M units are as close as $d_M(p)$.

like regression, propensity scoring, etc. also suffer this limitation. In regression analysis, the problem of unobservables is usually addressed via instrumental variables or the introduction of a dummy for each economic agent and each time period. These fixes are highly reliant on the quality of the instruments and the absence of economic unit varying, time varying unobservable components.

[12]The key advantage of time varying matching is that if observable factors like unemployment, and number of residents without automobile changes over time for the same treated market (as is the case in the current setting), it will trigger a different set of matching candidates that also reflect similar contemporaneous observable factor levels.

[13]Chrysler terminated all 749 dealers at the same time. Hence each city is flagged as a treated or a non-treated unit. Note that a city's treatment condition is time invariant. Treating each city-month combination as opposed to city alone as the unit of analysis allows me to also account for exogenously varying seasonality.

[14]Chevalier (1995) uses market-level average prices. In contrast, I use market-firm-time-specific outcome variables. This allows me to account for heterogeneous reactions by incumbent firms as well as heterogeneous reactions by the same incumbent firm across geographic markets.

Formally, $d_M(p) > 0$ is the real number satisfying:

$$\sum_{k:W_k=1-W_p} 1\left\{\left\|X_p - X_k\right\|_v < d_M(p)\right\} < M$$

and

$$\sum_{k:W_k=1-W_p} 1\left\{\left\|X_p - X_k\right\|_v \leq d_M(p)\right\} \geq M$$

where $1\{.\}$ is the indicator function, equal to one if the expression in brackets is true, and zero otherwise. Let $J_M(p)$ denote the set of indices for the matches for unit p that are at least as close as the Mth match:

$$J_M(p) = \left\{k = 1, ...N | W_k = 1 - W_p, \left\|X_p - X_k\right\|_v \leq d_M(p)\right\}.$$

If there are no ties, the number of elements in $J_M(p)$ is M, but in practice it may be larger. Let the number of elements of $J_M(p)$ be denoted by $\#J_M(p)$. Finally, let $Z_M(p)$ denote the number of times unit p is a match for other units, and $Z_M^{'}(p)$ the sum of the squared weights in the matches:

$$Z_M(p) = \sum_{k=1}^{N} 1\left\{p \in J_M(k)\right\} \frac{1}{\#J_M(k)},$$

$$Z_M^{'}(p) = \sum_{k=1}^{N} 1\left\{p \in J_M(k)\right\} \left(\frac{1}{\#J_M(k)}\right)^2.$$

For each economic unit p, there are two potential outcomes. One is observed, and the other is not. The observed outcome is its own estimate. The unobserved outcome is estimated by averaging the outcomes of the other most similar economic units who did choose this outcome. That is:

$$\hat{Y}_p(0) = \begin{cases} Y_p & \text{if } W_p = 0 \\ \frac{1}{\#J_M(p)} \sum_{k \in J_M(p)} Y_k & \text{if } W_p = 1 \end{cases},$$

and

$$\hat{Y}_p(1) = \begin{cases} \frac{1}{\#J_M(p)} \sum_{k \in J_M(p)} Y_k & \text{if } W_p = 0 \\ Y_p & \text{if } W_p = 1 \end{cases}.$$

The matching estimator to recover the average treatment effect is given by:

$$\hat{\tau}_M = \frac{1}{N} \sum_{p=1}^{N} \left(\hat{Y}_p(1) - \hat{Y}_p(0) \right) = \frac{1}{N} \sum_{p=1}^{N} (2W_p - 1) \left[1 + Z_M(p) \right] Y_p.$$

In practice, the matching estimator will be biased in finite samples when the matching is not exact. Abadie and Imbens (2002) offer a way to remove some of this bias term that remains after the matching. The bias-corrected matching estimator adjusts the difference within the matches for the differences in their covariate values. The adjustment is based on an estimate of the two regression functions $\mu_w(x) = E[Y(w)|X = x]$. Given the estimated regression functions, I predict the missing potential outcomes as:

$$\tilde{Y}_p(0) = \begin{cases} Y_p & \text{if } W_p = 0 \\ \frac{1}{\#J_M(p)} \sum_{k \in J_M(p)} \left[Y_k + \hat{\mu}_{\text{untreated}}(X_p) - \hat{\mu}_{\text{untreated}}(X_k) \right] & \text{if } W_p = 1 \end{cases}$$

and

$$\tilde{Y}_p(1) = \begin{cases} \frac{1}{\#J_M(p)} \sum_{k \in J_M(p)} \left[Y_k + \hat{\mu}_{\text{treated}}(X_p) - \hat{\mu}_{\text{treated}}(X_k) \right] & \text{if } W_i = 0 \\ Y_p & \text{if } W_i = 1 \end{cases}.$$

The bias-corrected matching estimator to recover the sample level average treatment effect is given by:

$$\tilde{\tau}_M = \frac{1}{N} \sum_{p=1}^{N} \left[\tilde{Y}_p(1) - \tilde{Y}_p(0) \right].$$

Table 1 is a stylized example to demonstrate the working of the simple matching estimator (i.e. without bias correction). For expositional purposes, I will abstract away product and product category identities. Suppose there is one city-specific outcome variable denoted Y, and a unidimensional city-specific time-varying covariate X on which the matching is done, and we track both of these variables for eight cities, each for three time periods. Cities $\{1,2,3\}$ see a Chrysler LLC dealership termination, but the brand affiliations of the terminated dealer vary across the three cities. Observations associated with cities $\{4,5,6,7,8\}$ are non-treatment condition candidates for matching if we are trying to assess the impact of the treatment for the treated cities. As is evidenced in the table, the estimator will use city 7 as a match for city 1 (which sees a Chrysler brand dealer termination), in time period 1 and city 6 as a match in time period 2. Since these are single candidate matches, the predicted outcomes for city 1 in period 1 and 2, if it were not to have seen a Chrysler termination, is given by observed values of $Y(0)$ for city 7 and city 6 in periods 1 and 2, respectively. In instances when we observe ties (e.g. city 2, time period 3), the predicted outcome given the treatment for this unit is equal to the average of the outcomes for matched non-treated units. Note that the matching estimator allows repetition.

In the discussion that follows, the unit of analysis (p) is generalized to a brand-category-city-time combination. For each brand-category-city-time combination the matching estimator will estimate, conditioned on observed covariates, the predicted outcome by averaging the observed outcome of the qualified matching observations. Correspondingly, the average treatment effect at the brand-category level is the average recovered treatment effect for that brand-category pair.

The data contain nine brands (Chevrolet, Ford, Chrysler, Jeep, Dodge, Mazda, Toyota, Nissan and Honda) spanning eight product categories (convertible, coupe, hatchback, sedan, SUV, truck, van and wagon). The covariates on which I do the matching include brand, category, time period, gasoline price, percent employed, percent without a vehicle, population, average household income, and population density.

In the actual analysis, I require an exact match on brand, category and time period. The reason for an exact match on brand and category is that I am interested in brand-category as the unit of analysis. I use an exact match on time period in order to account for the confounding effects of seasonality and other time varying factors within a market.

The outcome variables I study include (i) three marketing mix elements (i.e. price, assortment size and inventory), and (ii) brand-category unit sales. Price here is the log of brand-category specific time and city varying retail price. Assortment size is operationalized as the average number of unique models (i.e. nameplates) carried by incumbents selling a specific brand-category. Inventory is the total number of automobiles of that product carried by the dealer. In the section that follows, I review the key findings of the empirical analysis.

2.5 Results

The model outlined in section 4 is calibrated using the data described in section 3. Recall that I am interested in recovering the impact of Chrysler LLC dealer closings on incumbent dealers' pricing, inventory, and assortment size decisions and correspondingly on their unit sales. In the analysis, each incumbent is a brand-product pair. The bias-corrected matching estimator allows me to estimate the four focal variables for the incumbents had the Chrysler LLC terminations not happened.

As described in the model section, the treatment effect can be recovered for the overall sample (pooled across all incumbents). While the overall sample treatment effect is valuable in itself, if the underlying incumbents are highly differentiated (as is the case with automobiles), then the overall treatment effect may suffer serious aggregation bias. Therefore, I estimate the treatment effect for each incumbent.

Previous studies investigating the automobile industry have demonstrated significant across brand and product category asymmetries (Berry et al. 1995; Sudhir 2001; Goldberg and Verboven 2001). Based on these findings, one might expect the incumbent reaction to Chrysler LLC terminations also to vary across incumbent brands and product categories. For example, Chevrolet and Chrysler may be closer substitutes in the sedan category and less so in the SUV category. If this were indeed the case, one might expect Chevrolet sedan dealers to react more to Chrysler terminations than Chevrolet SUV dealers.

Recall that I conduct the analysis by brand-category pair. Estimating the treatment effect for each brand-category pair will not only change the composition of the treatment markets, but also the corresponding matches used to recover the treatment effect. Therefore the resulting treatment effect for each brand-category pair may vary by the brand affiliation of the terminated dealer.

Since I have nine brands and eight product categories, and not all brands have presence in all product categories, I recover a total of 60 treatment effects. However, once I account for treatment heterogeneity, the number of recovered treatment effects increases to 166. Rather than generating tables with the highest level of detail, I summarize the recovered brand-category level treatment effects across various dimensions. These are reported in Tables 6 through 13.

2.5.1 Effects by Product Category

Tables 6 and 7 summarize the treatment effects by product category (along rows) for each focal variable (in columns). Table 6 contains the incidence rates, i.e. what fraction of the brands within each product category respond in a statistically significant way, to Chrysler LLC dealer terminations.

For each focal variable, I report the overall statistically significant incidence rate in the first column, followed by statistically significant incidence rates based on the direction of the reaction in columns two and three. For example, when it comes to price, all brands that sell sedans react in a statistically significant way to at least one of the three Chrysler LLC brand terminations. The reaction of the same sedan brand can, however, vary with the identity of the terminated brand. For example, it is possible that Toyota sedan dealers react to one or more of the three terminations. But, conditional on the terminated brand, only a subset of Toyota sedan price reactions are significant, and of these, some are positive and some negative.

For example, while all sedan brands do react in price to at least one of the three brand terminations, conditional on the brand affiliation of the terminated dealer, 78 percent of the sedan brands responded to one of the brand terminations by increasing prices, while 56 percent responded by decreasing prices. Similarly, 78 percent of the sedan brands responded in a statistically significant way to one of the Chrysler LLC terminations by altering their assortment size. However, conditional on the brand affiliation of the terminated dealer, 56 percent of the sedan selling brands increased their assortment size, and 56 percent decreased their assortment size. It is worth noting that none of the convertible brands reacted to Chrysler LLC terminations, nor do they see any statistically significant impact on unit sales. This is partly due to the limited number of observations I have to recover the related treatment effects (see Table 3). On average, the results suggest that incumbent brands react most often to Chrysler LLC terminations by changing their retail prices, followed by inventory and assortment size.

The frequency with which they respond in the marketing mix varies significantly across product categories. Sedans and SUVs respond most frequently, while wagons have the lowest reaction rates. Within the same marketing mix element, e.g. price, we notice significant heterogeneity in treatment effects across product categories. I find that sedan brands not only react most often in price, but do so most often by increasing retail price. Most truck brands (71 percent) also react, but do so most often by reducing the retail price (57 percent). For assortment size, the highest incidence of increase is observed for the SUV category, whereas the highest incidence of decrease happens for the sedan category. For inventory, the highest incidence of increase and decrease is observed for the sedan category.[15] When it comes to unit sales, changes are observed most frequently with SUVs, followed by trucks and sedans. The highest incidence of unit sales increase is seen for sedans and trucks, while the highest decrease is observed for SUVs.

While I report incidence rates in Table 6, I characterize the magnitude of the incumbent reactions by product category in Table 7. The reporting structure is akin to Table 6. For example, of all of the sedan brands that did react to any Chrysler LLC brand termination, their mean price reaction is 4.16 percent (averaged across all statistically significant positive and negative reactions, across all incumbent brands and terminated brand affiliations). The average of the statistically significant and positive sedan price reactions is 8.30 percent. The average of the statistically significant and negative sedan price reactions is -7.05 percent. On average, the highest price increase is observed for vans (6.08 percent) and SUVs (4.50 percent), while the highest decrease in price is observed for the wagons (-5.37 percent) and trucks (-4.42 percent).

[15] This is possible because I assume that there is a significant reaction if there is at least one significant reaction to a Chrysler, Dodge, or Jeep exit. For example, in some cases, there may be a positive reaction to a Chrysler exit and a negative reaction to a Dodge exit for the same category.

The highest assortment size increase is observed for SUVs (0.70 units), and the highest decrease in assortment size is observed for hatchbacks (0.54 units). When it comes to dealer inventory, incumbent dealers who sell wagons experience the highest increase (1.64 units), while sedan dealers have the largest reduction in monthly inventory (-15.50 units). When it comes to the resulting impact on unit sales, the highest sales increase is observed for sedans (6.64 units) and coupes (5.69 units), and the highest decrease in unit sales is observed for SUVs (-4.56 units).

2.5.2 Effects by Incumbent Brand

In order to assess inter-brand differences in reactions to Chrysler LLC terminations, in Tables 8 and 9 I summarize the treatment effects by incumbent brand, i.e. brand-specific treatment effects summarized across all its product categories and across all three Chrysler LLC brand terminations. I group the brands by country of origin to see if domestic brands react differently to Chrysler LLC dealer distribution network consolidations than their foreign counterparts.

Table 8 contains the incidence rates of the incumbent reactions to the Chrysler LLC terminations by brand (row variable). In the columns, I summarize these effects by a focal outcome variable. For each outcome variable, in the first column I report the overall incidence rate (across all categories and Chrysler LLC brand terminations) for the same brand (row identifier).

As one can see from the table, there exist substantial differences in incumbents' reactions across brands. Ford, Nissan, and Toyota have the highest incidence of marketing mix reactions, whereas Mazda and Honda have the lowest. The highest incidence of price increases is observed for Chevrolet (63 percent) and Toyota (63 percent), whereas the highest incidence of price decrease happens for Nissan (88 percent). The highest incidence of assortment size increase is observed for Ford, Chevrolet, Nissan and Jeep (50 percent), whereas the highest incidence of assortment size decrease happens for Ford (63 percent) and Toyota (50 percent). The highest incidence of inventory increases is observed for Nissan (63 percent), whereas the highest incidence of inventory decreases happens for Honda (57 percent) and Toyota (63 percent). When it comes to sales, the incidence is most frequent for Toyota and Ford, followed by Jeep and Chevrolet. The highest incidence of increases is seen for Jeep, Chevrolet and Toyota, while the highest decreases are observed for the same brands.

Taken together, domestic brands have a higher incidence of price increases and a lower incidence of price decreases compared to their Japanese counterparts. American brands have a higher incidence of assortment size increases and a lower incidence of assortment size decreases compared to the four Japanese brands. American brands experience a higher incidence of inventory reduction compared to Japanese brands. American brands also see higher rates of increases and reductions in unit sales. However, much to my surprise, when I ignore the direction of the reactions, on average, and when it comes to incidence rates alone, domestic brands reacts very similarly to their Japanese competitors.

In Table 9, I summarize the magnitude of the brand-specific reactions (pooled across all underlying categories and three Chrysler LLC brand terminations). Consistent with the objectives outlined by Chrysler LLC in its bankruptcy restructuring plans, I find that, on average, the highest price increases are observed for Chrysler, Chevrolet and Jeep, the three Chrysler LLC brands. The highest price decreases happen for Nissan and Ford. On average, the highest assortment size increases are observed for Jeep, Dodge, and Chevrolet, whereas Toyota and Ford see the highest assortment size reductions. Jeep, Ford, and Nissan see the highest inventory increases, while Honda and Toyota see the highest inventory reductions. On average, the highest sales increases are observed for Chevrolet, Chrysler, and Jeep, whereas the highest sales decreases happen for Ford, Toyota, and Nissan.

While the overall reactions do not differ very much based on incidence rates (see Table 8), when I compare the effect sizes, I find significant differences. For example, on average, domestic brands increase their retail prices, increase assortment size, increase their inventory and see an increase in unit sales. Japanese brands, on the other hand, decrease their retail prices, decrease their assortment size, decrease their inventory and experience a decrease in unit sales.

2.5.3 Effects by the Identity of the Terminated Dealer

So far I have not explored how the incumbent recovered treatment effects vary across the three treatment conditions, i.e. the identity of the terminated dealer. Given its significance to the central research question of this study, next I characterize these reactions. I begin first by summarizing the treatment effects for each focal outcome variable by terminated brand. I later decompose these effects by underlying incumbent brand.

In Tables 10 and 11, I summarize the results by terminated brand. Table 10 contains the overall incidence rates and incidence rates by direction of the incumbent reaction. As shown in Table 10, for the same terminated brand there are both positive and negative reactions within the same marketing mix element. This is because of the heterogeneity in reactions of the incumbent brands and for the same brand across product categories.

For example, when the terminated dealer is a Chrysler brand dealership, incumbents most often increase their retail prices and reduce their assortment size and retail inventory. However, when the terminated dealer is a Dodge brand dealership, incumbents mostly decrease their prices and increase their assortment size and dealer inventory. When a Jeep dealer gets terminated, incumbents increase their retail prices and assortment size but reduce their inventory. When it comes to unit sales, when a Dodge dealer gets terminated, unit sales increase for most incumbents. But when a Chrysler dealer exits, unit sales drop for most incumbents.

When I look at the extent of the incumbent reactions, I find that retail prices increase most when a Jeep dealership is terminated and decrease the most when a Dodge dealership is terminated (see Table 11). Incumbents increase their assortment and inventory the most when a Jeep dealership is terminated and reduce both significantly when a Chrysler dealer is terminated. Unit sales increase most when a Dodge dealer is terminated and decrease most when a Chrysler dealer is terminated.

2.5.4 Effects by Terminated Dealer-Incumbent Brand Combination

What is still unanswered so far is how incumbent reactions vary by a terminated dealer's brand affiliation and across the four outcome variables. To answer this, I summarize the treatment effects by terminated brand and incumbent brand in Tables 12 and 13.

Table 12 contains the incidence rates and incidence rates by direction of the incumbent brand reactions. As conjectured, I find that the reactions of incumbent brands vary significantly with the brand affiliation of the terminated dealer. For example, when it comes to the incidence of the price reaction, incumbent Nissan dealerships do not respond to a Chrysler brand termination, but do react to a Dodge termination. Ford responds with changes to assortment size and retail inventory most often when a Chrysler dealership is terminated and far less so when the terminated dealer is a Dodge dealership. When I contrast the incidence rates for domestic and Japanese brands, the results reveal that domestic brands react more often to a Jeep or Chrysler termination and less to a Dodge dealer termination than their Japanese competitors.

How about the magnitude of the incumbent reactions? Do they vary by terminated brand? To answer this question, I summarize the effect sizes of treatment effects by terminated brand in Table 13. Here, too, I find significant differences in incumbent reactions both across incumbent brands and for the same incumbent brand across the brand affiliation of the terminated dealership. For example, Chevrolet increases its retail price most when a Dodge dealership gets terminated and least when a Chrysler dealership is closed. Even the magnitude of the incumbent brands' assortment size reaction varies with the brand of the terminated dealer. For example, Ford decreases its assortment size when a Chrysler dealership is terminated, but increases its assortment when either a Jeep or Dodge dealership is terminated.

Lastly, when I compare the magnitude of the incumbent reactions grouped by country of origin against terminated brand, the results offer valuable insights. On average, the reactions of both the domestic brands and the Japanese brands are directionally equivalent when the terminated dealer is a Chrysler dealership. But the magnitude of their reactions to Chrysler brand terminations does vary. When I examine the reactions to Dodge or Jeep terminations, the difference between domestic brand and Japanese brand reactions is far more stark.

For example, American brands increase their prices when a Dodge dealership gets terminated, but their Japanese counterparts decrease their prices. However, when a Jeep dealership gets terminated, the reactions are just the opposite. Here, domestic brands reduce their prices, while Japanese brands increase their retail prices. When it comes to assortment size, domestic brands increase their assortment when a Dodge dealership is terminated, while the Japanese brands decrease their assortment size. Both domestic and Japanese brands, however, increase their assortment size when a Jeep dealership is terminated.

2.6 Conclusions and Directions for Future Research

The empirical analyses conducted so far reveal very interesting patterns and provide a rich new lens to study inter-brand competition in the U.S. automobile industry pre- and post-Chrysler LLC bankruptcies. This is achieved by exploiting rich institutional features of this industry and evaluating the economic implications of a large structural change in the market, i.e. Chrysler LLC dealer network consolidation.

Given the economic significance that the automobile industry bears to the health of the U.S. economy and the recency of the studied marketplace changes, the insights developed so far have natural appeal to marketing managers and policy makers alike. Marketing managers can use the insights developed to understand how regional dealers of their brands reacted with their marketing mix to market structure changes induced by Chrysler LLC's dealer network consolidation. One can also assess the impact of these changes on category-specific brand sales.

The study is envisaged to be primarily descriptive, i.e. the purpose is largely to document what happened in response to Chrysler LLC terminations. Much ground has already been covered in this regard. However, as with all studies, this study, too, suffers limitations. These limitations are not critical to the descriptive purpose of this research endeavor.

My results demonstrate economically significant and statistically heterogeneous changes in incumbent dealers' marketing mix reactions and consumer demand post bankruptcy-induced Chrysler LLC terminations. These results raise the question of whether such changes are socially inefficient. A very valuable direction for future research is to assess the possible welfare implications on these incumbent reactions. For that, one needs to answer the question: why do dealers respond the way they do? To be able to deliver on this research objective would require one to undertake a structural analysis approach.

Equipped with a structural demand and supply side model, one could decompose the various economic-theory-driven motivations (described in section 1) for the incumbents' reactions. For example, some incumbents may be altering their marketing mix to attract consumers who may have otherwise been lost to the terminated dealer. Other incumbents may want to take advantage of a reduced number of competitors and choose to increase their retail margins (at the risk of selling fewer sales units), i.e. softer competition. There also may be some incumbents who are not directly reacting to the Chrysler LLC termination, but are reacting to other incumbents who are actually reacting directly to the Chrysler LLC termination, i.e. spillover.

While the first two reactions are directly tied to the terminations, the third is an indirect reaction. Such an analysis is beyond the scope of this study. Nonetheless, the current reduced form analysis combined with causal inference is a very good first stage descriptive exercise characterizing the marketplace shift as a result of the large change in Chrysler LLC's dealer distribution network.

It is also likely that observed consumer demand and incumbent reactions are impacted by dynamic considerations. For example, consumers may anticipate deep price discounts by incumbent dealers or "fire sales" by terminating dealers and time their purchases accordingly. In response dealers time their reactions and the depth of their reactions accordingly be they price, assortment size or inventory. What we observe in the data is the steady state equilibrium outcome. Accounting for dynamic considerations across several elements of the marketing mix, some of which are discrete (e.g. inventory and assortment) and some continuous (price), and undertaking causal inference to assess the impact of dealer network terminations is outside the scope of any one study.

Investigating the consumer side dynamics via a dynamic structural demand model to understand how dealer consolidation impacts consumer automobile adoption timing decisions is another fruitful area of future research. I take a first step in this regard with my second essay.

CHAPTER 3

Essay 2: How Does Chapter 11 Bankruptcy Impact Consumer Adoption? An Investigation of What-, When-, and Where-to-Buy Decisions

3.1 Introduction

3.1.1 Overview

The current global economic crisis has led to a historically high number of corporate bankruptcies and garnered renewed interest in understanding the broader economic implications of these bankruptcies. One of the most extensively used bankruptcy formats by businesses is Chapter 11 bankruptcy, whereby the financially distressed firm restructures itself under court supervision and reemerges, instead of exiting the market altogether. On average, 10,500 businesses file for Chapter 11 bankruptcy protection in the U.S. every year. Firms seeking this protection span a wide range of industries from auto manufacturers, financial services, and insurance providers to pharmaceutical manufacturers and airline carriers.

One of the most critical economic implications of bankruptcies is related to consumer demand. The theoretical literature on the economics of bankruptcies suggests that the bankrupt firm could face demand shocks that result in reduced demand for its products (Titman 1984; Opler and Titman 1994). Relatedly, some recent industry surveys have tried to uncover the impact of Chapter 11 bankruptcies on consumers' purchase decisions. A study of 6,000 consumers by CNW Marketing found that 80 percent of respondents said they would switch companies if General Motors (GM) or Ford filed for bankruptcy protection. 21 percent of the respondents in another poll conducted by the car buying site Cars.com said that automobile manufacturer bankruptcies would affect their decision on which company they would buy a car from. Yet there is scant research formally examining the size of these demand shocks in general or in case of durable goods (Hotchkiss et al. 2008).

The objective of this study is to fill this research gap by investigating the effect of Chapter 11 bankruptcy and related market exits on what, when, and where consumers buy using a unique data set from the U.S. auto industry. More precisely, this paper quantifies the impact of two important drivers of consumer purchase decisions that are expected to be affected by Chapter 11 bankruptcy:[1] *(1) brand equity* and (2) *distribution network structure*.

Chapter 11 bankruptcy may potentially affect the brand equity for the bankrupt firm for several reasons. In a durable good context, the consumption stream that the goods provide depends on services like warranties, parts replacement, maintenance, upgrades and finally trade-in in the used car market. Bankruptcy in such a setting threatens many of these after sales activities and as a result can substantially reduce the value of the distressed firm's products to its current and prospective customers.[2]

A bankrupt firm's brand equity can also be eroded as a result of the negative brand image it incurs from filing for bankruptcy protection. For example, Edmunds.com says "No one can blame car buyers who shied away from brands that were mentioned in the same breadth as the word bankruptcy."

Chapter 11 bankruptcy process may also positively impact the distressed firm's brand equity

[1] See for example the discussion at http://www.msnbc.msn.com/id/30520044/ns/business-autos/t/would-you-buy-car-chrysler/#.Tp272bJ2Wok.

[2] "GM refuses to repair 400,000 Chevrolet Impalas, says it's "Old GM's" responsibility" carscoop.blogspot.com.

because the reorganization process usually results in a firm with a leaner product line and lower costs. A more consolidated and lower cost firm can be perceived more favorably by consumers than its predecessor entity.[3] This is especially the case where the reorganization is supported by important stakeholders such as government.[4]

Given the aforementioned countervailing forces impacting the brand equity of the distressed firm, the net impact on brand equity of the bankrupt manufacturer remains an empirical question. However, a recent report by the Office of the Special Inspector General for the Troubled Asset Relief Program reveals that the Presidential Task Force, which was very actively involved in the Chapter 11 reorganization proceedings of Chrysler LLC and GM, believed that the restructuring efforts of GM and Chrysler LLC would positively impact the brand equity of the two automobile manufacturing giants and help sustain them in the long run (SIGTARP 2010). To the best of my knowledge, this claim is yet to be validated.

Chapter 11 bankruptcies often result in substantial changes to the distressed firm's distribution network structure as well. For example, in the U.S. auto industry, both Chrysler LLC and GM pruned 25 percent of their dealer network as part of their Chapter 11 reorganizations. Recent studies in the economics literature document similar network structure changes in the airline industry (Ciliberto and Schenone 2010).

Chapter 11 induced distribution network pruning can impact consumers' immediate and long-run purchase decisions. First, it changes the composition of products that consumers can purchase from their local dealers. Second, it impacts the set of dealers who continue to serve the local market. Lastly, it alters consumers' expectations about new product introductions and quality improvements in the near future.

The U.S. automobile industry is characterized by a steady stream of new product introductions, continued improvements in quality, and falling prices over the product life cycle. The price of a specific car falls quite precipitously when a similar car is introduced by a competing manufacturer or a modified version of the same car is introduced by the focal manufacturer (e.g.

[3]See consumer posts along those lines at http://answers.yahoo.com/question/index?qid=200903050607-15AAVS8aJ.

[4]For example, in the case of Chrysler LLC and GM bankruptcy reorganization, the U.S. government has tried to assure car owners and would-be buyers that the companies are going to continue operating and that their warranties are safe.

Levinthal and Purohit 1989; Purohit 1992). In doing so, dealers extract the maximum surplus from high valuation consumers early into a product's life cycle, and then lower prices over time to sell to the low valuation consumers remaining in the market. An informed forward-looking consumer may strategically delay her adoption and purchase the same car at lower price or better car at a higher place later.

Upon purchasing a new car, which is a durable good, consumers exit the market for a few years. During this time the purchased car depreciates in value and the consumer incurs additional costs like routine maintenance, parts replacement, recalls, etc. At the end, the consumer trades in the currently held automobile for another car or gets some scrap value for it. If post-purchase consumption stream costs are high (as is the case with automobiles), a consumer will tradeoff the total consumption stream costs (purchase, holding and reselling costs) across currently available and anticipated products, while making her new car purchase decisions. In the absence of consumption stream costs or falling prices with quality improvements, a consumer would choose a product that maximizes her utility in each period and she would have no incentive to look forward or hold the current car across multiple periods.

In order to capture these aforementioned institutional features of the automobile industry, I develop and estimate a dynamic structural model of consumer demand at the dealer-brand level for the new car market. Specifically the model allows me to assess the impact of Chapter 11 bankruptcy-induced brand equity and distribution network structure changes on consumers' what, where and when to buy decisions.

My empirical analysis shows that Chapter 11 bankruptcies of Chrysler LLC and GM had an economically significant impact of consumers' new car buying decisions. In the case of Chrysler LLC, its bankruptcy-induced distribution network pruning coupled with reduction in brand equity by filing for bankruptcy protection led 21 percent of its potential consumers (i.e. Dodge and Chrysler's consumers) to switch to competing automobile manufacturers.

Surprisingly, most of these consumers switch to Japanese brands such as Honda (9.22 percent) and Toyota (4.32 percent) as opposed to American brands such as Chevrolet (2.81 percent) and Ford (0.25 percent). An additional four percent of Chrysler LLC's prospective customers deferred their new car purchase altogether.

In contrast to the Chrysler LLC's loss from bankruptcy filing, GM gains after the period of Chapter 11 bankruptcy protection. GM gains because of a net increase in its brand equity in the post-bankruptcy time period. As a result, two percent of the prospective consumers of competitor brands switch to GM's Chevrolet brand. Specifically, Honda (1.5 percent), Toyota (0.3 percent), Nissan (0.15 percent), and Ford (0.14 percent) lose market share to GM after GM emerges from bankruptcy.

The decomposition of Chrysler LLC's brand level market share changes into contributions from (1) changes in brand equity and (2) distribution network pruning reveals additional interesting insights. 15.8 percent of Dodge's loss come from reduction in Chrysler LLC's distribution network and only 0.1 percent from reduction in Chrysler LLC's brand equity. In contrast, 1.74 percent of Chrysler brand's losses come from reduction in Chrysler LLC's distribution network and 7.96 percent from decrease in Chrysler LLC's brand equity. In other words, the relative effects of changes in brand equity and changes in distribution network vary across brands in Chrysler LLC's portfolio.

Decomposition of market share gains by competitor brands reveal that competing manufacturers of Chrysler LLC accrued most of their gains from Chrysler LLC's distribution network pruning (e.g. Honda 7.9 percent, Toyota 2.97 percent, and Chevrolet 2.74 percent). Their gains from reduction in Chrysler LLC's brand equity is quite small (e.g. Honda 1.32 percent, Toyota 1.35 percent, and Chevrolet 0.07 percent). Only Hyundai gains more from reduction in Chrysler LLC's brand equity (1.3 percent vs. 0.58 percent).

3.1.2 Contribution of This Study

This study makes several substantive and methodological contributions. Unlike the extant literature which has predominantly focused on the supply side implications of corporate bankruptcies, this study is the first to empirically examine the consumer side. Specifically, previous research looks at variables such as marketing mix elements (Borenstein and Rose 1995; Öztürk et al. 2011), service level (Borenstein and Rose 2003) and capacity (Ciliberto and Schenone 2010) (see Table 14).

Moreover, these studies take a reduced form approach to describe what happens as a result of bankruptcy filings, but they do not explicitly model the structural drivers that led to the outcome. In contrast, this paper takes a structural approach in order to provide microeconomic theory driven explanation for changes in market outcomes. It is the first paper to propose a dynamic structural model of consumer adoption to quantify the differential impact of bankruptcy-induced changes to the distressed firm's brand equity and distribution network.

To the best of my knowledge, this is the first study to calibrate a retailer level dynamic structural durable goods adoption model with spatially differentiated retailers and spatially dispersed consumers using aggregate data.[5] The emerging literature on the estimation of dynamic models of demand for differentiated products (Melnikov 2001; Gowrisankaran and Rysman 2009; Schiraldi 2011) take into account several key drivers of dynamic consumer adoption behavior, including rational expectations about future products, persistent heterogeneous consumer tastes, repeat purchases, and the existence of secondary markets. These studies use aggregated national level data at the product level as opposed to retailer-product level, and hence cannot accommodate the role of geographic differentiation on consumers' durable goods adoption decisions.

This is incredibly important in my empirical setting, since distribution network pruning can have heterogeneous impact across consumers within the same local market. For example, the impact can be much more significant for a consumer whose most preferred dealer is terminated than a consumer whose less preferred dealer is terminated.

This paper extends the methodology proposed by Gowrisankaran and Rysman (2009) and complements the approach in Schiraldi (2011) through the inclusion of deterministic product depreciation and advancing an alternate importance sampling procedure. Specifically, this study uses individual level online search data to conduct importance sampling. The search data include the zip code of the searcher, brands and models searched, including the order of search and any distance constraints imposed as part of the search query (e.g. dealers within five miles of a specific zip code, etc.). The click-stream search data are leveraged to generate a spatial

[5] There exist previous studies that model retail demand incorporating the locations of retailers and the geographic distribution of consumers within a market (e.g. Davis 2006). However, they estimate a static choice model.

empirical distribution of "consumer interest," which in turn is used to sample consumer types. To my knowledge, this is the first study to combine aggregate sales data and disaggregate online search data to calibrate a dynamic structural durable goods adoption model (see Table 15 for a summary of a comparison of this study with similar studies in the literature on the estimation of dynamic models of demand using aggregate data).

The rest of the paper is organized as follows. In the next section, I briefly review Chapter 11 bankruptcy reorganization and provide specifics on the two focal bankruptcies studied in this paper, i.e. Chrsysler LLC and General Motors bankruptcy filings in April 2009 and June 2009, respectively. In the third section, I review the extant economics of bankruptcies literature. This is followed by a description of the data used in my empirical analyses while offering some model free evidence to motivate the key modeling elements of my demand model developed in the fourth section. In the fifth section, I discuss the proposed model and review the estimation procedure highlighting key advancements. I review the estimation results in the sixth section, which is followed by the counterfactual simulations. The last section concludes with a summary of my findings and directions for future research.

3.2 Background Information

3.2.1 Chapter 11 Bankruptcy Reorganization

Chapter 11, named after U.S. bankruptcy code 11, is a form of bankruptcy that provides protection to financially distressed debtors (usually a corporation or partnership). Given its complexity and costs, Chapter 11 bankruptcy is mostly preferred by large firms. It affords the bankrupt firm a number of mechanisms to restructure its business so that it can continue operation. These mechanisms involve debt and capital restructuring, supply and labor contract negotiation, as well as product line consolidation.

Chapter 11 bankruptcy process starts with the creation of a restructuring plan by the debtor or debtors involved. Creditors may propose modifications to the proposed plan. Any plan that is advanced by the debtor must be approved by the creditors, and if there are alternative plans sometimes the creditors are given the opportunity to vote on the plan that is going to be undertaken. A trustee will supervise the entire reorganization process. The trustee monitors the reorganization process in order to ensure that assets are managed properly and that operating reports and fees conform with the bankruptcy procedures. If the debtors are not managing the assets properly, the trustee may take more control or designate someone else in charge of the distressed firm's assets. Depending on the extent of the financial distress and the size of the bankrupt firm, the time frame for a firm to emerge from bankruptcy can vary from a few months (e.g. Pan American Airways Corp.) to a few years (e.g. Continental Airlines).

3.2.2 Chapter 11 Bankruptcies in the U.S. Auto Industry

The automotive industry is an important pillar of the U.S. economy. The "Detroit Three" - i.e. General Motors, Ford and Chrysler - alone employ 880,000 workers (6.6 percent of the U.S. manufacturing workforce) and contribute approximately 3.6 percent or $500 billion to the total GDP output. In the U.S., transactions at automobile dealerships account for a staggering 19 percent of all retail sales – making it the largest single retail sector and outpacing general merchandise stores, food and beverage stores, and even gas stations (Figure 1). Any major structural changes in this industry have a profound impact on the country's economy. Given its economic significance and rich institutional features, the automobile industry has had natural appeal to marketing scholars (e.g. Desai and Purohit 1998; Sudhir 2001; Albuquerque and Bronnenberg 2010).

The current global recession, which began in 2008, sent shock waves through every sector of the economy. The economic meltdown arguably had the swiftest and most disastrous effect on the auto industry, which lost 50 percent of its sales volume in a single year and slashed 400,000 jobs. Recession concerns, rising unemployment, gas price shocks and the liquidity crisis led consumers to pull back on their automobile purchases and rethink their love affair with vehicles that had relatively low fuel economy, but which had been the bedrock of profits for the Detroit Three since the early 1990s.

In September 2008, the financial woes of the automobile industry reached panic proportions. The demise of the sub-prime mortgage market and uncertainty about future losses on illiquid and complex assets held by the financial institutions resulted in equity borrowing firms having reduced access to private liquidity. The loss in liquidity and the swift demise of credit markets proved fatal for the automobile industry because:

1. auto sales are heavily dependent on adequate financing for dealers and consumers, and

2. GM and Chrysler LLC were already in a precarious financial state before the Fall of 2008. The tightening of credit made it impossible for them to raise private funds to keep their operations afloat. Even the injection of capital from the U.S. federal government did not help.

The crisis forced auto manufacturers and government regulators to make decisions in real time about how to keep the industry competitive. It also focused attention on the unique restrictions that government had placed on this industry that hampered its ability to quickly adjust to new marketplace realities. For example, union contracts prevented car manufacturers from closing down factories (SIGTARP 2010) and state franchise laws prevented them from closing down dealerships. The only way out was bankruptcy (Lafontaine and Morton 2010).

By 2009, two of America's three car manufacturers exercised their last-ditch option, making GM and Chrysler LLC the first U.S. auto manufacturers in history to file for Chapter 11 bankruptcy. The move gave Chrysler LLC the freedom to immediately terminate 789 – or 25 percent – of its 3,181 dealerships. It also gave scholars unique new opportunities for inquiry.

Such large scale distribution strategy changes were unprecedented in the auto industry, raising research questions that were previously not testable. For example, how did bankruptcy-induced large scale distribution channel pruning by Chrysler LLC impact consumers' new car adoption decisions? Did the Chrysler LLC's distribution channel pruning help increase Chrysler LLC's own market share due to tempered intra-firm competition? Did Chrysler LLC's rivals gain market share as a result of Chrysler LLC's bankruptcy-induced woes?

With these two economically significant bankruptcies as my backdrop, I study the differential impact of Chapter 11 bankruptcy-induced (1) changes in Chrysler LLC and GM's brand equity and (2) Chrysler LLC's distribution network pruning (see Figure 3) on forward-looking consumers' new car purchase decisions.

3.3 Literature Review

The emerging literature that looks at the effect of bankruptcy filings on market outcomes focuses on supply side outcomes such as marketing mix elements (Borenstein and Rose 1995; Öztürk et al. 2011), service level (Borenstein and Rose 2003) and capacity (Ciliberto and Schenone 2010). These studies take a reduced form approach to describe what happens as a result of bankruptcy filings, but they do not explicitly model the structural drivers that led to the outcome.

For example, Borenstein and Rose (1995) find that firms on average reduce their prices by five to six percent prior to a bankruptcy filing, but do not further cut fares subsequent to entering Chapter 11 bankruptcy in the context of airline industry. In the auto industry setting, Öztürk et al. (2011) show that incumbent dealers react to Chapter 11 induced dealer closings by changing prices, followed by changing their inventory, and lastly assortment. They also find that surviving dealerships of the auto manufacturer that declared bankruptcy uniformly increase prices, but show the same mixed reactions as rival manufacturers' dealerships when it comes to inventory and assortment. To the best of my knowledge, there is no research that investigates the impact of Chapter 11 bankruptcy on consumer side outcomes. This study addresses this research gap. I take a structural approach and conduct a microeconomic theory-driven investigation of consumer side reactions to Chapter 11 bankruptcies of durable goods manufacturers.

Starting with Coase (1972), there exists a large theoretical literature (Stokey 1979, 1981; Bulow 1982; Moorthy 1988; Narasimhan 1989; Besanko and Winston 1990; Balachander and Srinivasan 1998; Desai and Purohit 1999) analyzing the pricing of durable goods in markets with forward-looking consumers. However, the role of distribution channels and therefore changes in its structure have been overlooked by this literature. Empirical research has primarily focused on examining the extent to which consumers' forward-looking behavior affects firms' prices and profits (Melnikov 2001; Nair 2007; Lee 2008; Gordon 2009; Gowrisankaran and Rysman 2009; Schiraldi 2011). These studies are primarily calibrated using national level panel data, which limit their ability to generate predictions on how retail distribution channel changes impact consumers' durable good adoption decisions. Given these limitations, neither the extant theoretical nor the empirical literature on durable goods adoption directly speak to the link between distribution channels and consumers' durable good adoption decisions.

In contrast to previous empirical studies of durable good adoption, I calibrate my model using a rich new database containing retailer level (dealer level) monthly data on prices, sales and time-varying product characteristics along with individual level online search data. Access to these data affords me a rare new opportunity to investigate aforementioned distribution channel pertinent research questions not addressed in the previous literature. Availability of dealer level data helps me identify the effect of spatial differentiation. I augment these data with zip code level online search data to control for spatially dispersed consumers' innate interest in purchasing a new cars.

3.4 Data

The data used in this paper contain dealer-brand level monthly new car sales. These data span the period from January 2008 to August 2010 for the Las Vegas, Nevada market. There are several reasons why I chose this market. First, the use of a local market level analysis is appropriate given the study's focus on distribution related changes (i.e. changes in the spatial structure of the market). Second, four Chrysler LLC dealerships were closed as a result of Chapter 11 bankruptcy reorganization in this market. Third, a clear market definition is critical to any structural analysis. In this regard, geographically isolated markets are much preferred since these impose natural constraints on distances to which consumers travel to engage in economic trade. The closest neighboring area with a dealership outside the Las Vegas metropolitan statistical area is 75 miles away. This geographic feature of Las Vegas makes it even more attractive for my analysis (see Figure 4). Finally, incumbent dealers in this market sell most of the main brands, including Chrysler, Chevrolet, Dodge, Ford, Toyota, Honda, Nissan, Hyundai, and Volkswagen. This allows me to assess consumer tradeoffs across most brands in the market.

I treat each dealer-make-model-type-year combination (e.g. 2008 Honda Accord Sedan at dealer X) as the unit of observation. The data set has information on unit sales, price, and product characteristics of all new cars sold by each dealer in each month. These data were obtained from a large market research firm synonymous with the automobile industry. The firm also provided information on dealer characteristics (physical street address and name of the dealership) and VIN level product characteristics, including the manufacturer, make, and type (e.g. sedan, hatchback) of the car, and whether the car is a hybrid. I use the physical street addresses to generate the latitude and longitude data for each dealer.

To augment these data with additional product characteristics, I collected size and horsepower data from www.autos.aol.com. Miles per gallon information for each make-model-year combination were obtained from www.epa.gov. Information about reliability is obtained from the overall mechanical quality rating from www.JDPower.com. To account for changing fuel prices, I gather the price of gasoline from the U.S. Energy Information Administration. I combine these data to create a miles per dollar (MP$) measure which is calculated as the miles per gallon divided by price per gallon. I deflated all prices using the Consumer Price Index released by the Bureau of Labor Statistics to January 2008 dollars.

Last, but not least, I collected consumer level session by session online search data. These search data contain information on the zip code of the consumer engaged in online search, brands and models searched including the order in which they are searched, and any geographic distance constraints imposed as part of the search query. Figure 5 suggests that online search data could provide additional information about consumer interest in buying a new car over and above using the empirical population density as is done in Houde (2011). Therefore I aggregate my search data to generate a zip code level empirical distribution of “consumer interest,” which in turn is used to fine tune the consumer level choice probabilities in my importance sampling procedure (more details on this are contained in Section 5).

In the empirical analysis, I focus on the market for passenger cars and limit the products to the sedan and hatchback categories. The reason for this is threefold. First, limiting to these categories drastically alleviate the computational burden of estimating an already computationally demanding dynamic structural adoption model. These are also the product categories with the highest market penetration. Lastly, during the time frame of our analysis, these categories contributed most to the manufacturer's bottom line as rising gas prices led consumers to switch away from large gas guzzling alternatives. Table 16 provides summary statistics of key variables used in my empirical analysis.

I report the market share changes for select brands and dealers between the before and after Chapter 11 bankruptcy time period (Figure 6). As can be seen, there are noticeably large changes in market shares both within and across brands of the bankrupt manufacturers before and after filing for Chapter 11 bankruptcy protection. Interestingly, whereas Chrysler LLC brands (Chrysler and Dodge) lose market share after bankruptcy, Chevrolet (a GM brand) gains market share. These brand level market share changes clearly call for an analysis to be conducted at least at the brand level.

Dealer level variations in the market share for two of Chrysler LLC dealers shown in Figure 6 indicate that different dealers of the same brand face heterogeneous outcomes. One reason for this heterogeneity could be the variation in the distance between the surviving Chrysler LLC dealers to the bankruptcy induced terminated Chrysler LLC dealers. These differences may also stem from differences in the composition of products carried. These market share differences may also be impacted by marketing mix differences across these dealers. Last, but not least, these heterogeneous outcomes may also be grounded in the composition of patrons that each dealer draws to the dealership.

These heterogeneous within manufacturer across dealer outcomes warrant that the analysis be conducted at the individual dealer level. Taken together, my model free evidence suggests that any analysis conducted at the level of the manufacturer alone or brand market level alone can limit our understanding of the competitive landscape and the underlying tradeoffs that consumers make while purchasing new cars.

3.5 Model and Inference

In this section, I review my dynamic structural demand model, discuss modeling assumptions, and outline the key building blocks of my estimation procedure.

3.5.1 Model Setup

Similar to Gowrisankaran and Rysman (2009), I consider the following consumer level infinite horizon dynamic optimization problem with a discount factor β. At each time period t (month in this case), each consumer i chooses either one of the currently available products, J_t, or chooses to defer purchase to a future period and continue to use the currently owned car or avail of other mode of transportation. Similarly, at period $t+1$, the consumer chooses one of the J_{t+1} products or opts for the outside option $j = 0$ so that she maximizes the sum of the expected discounted value of utilities conditional on her information at period t.

Each product $j \in J_t$ is characterized by observed characteristics x_{jt} (e.g. manufacturer, size, reliability, etc.), the unobserved (by the econometrician) characteristic ξ_{jt}, and the price p_{jt}. Extending Gowrisankaran and Rysman (2009), I assume that products deterministically depreciate at a rate of λ.[6] I assume that consumers are heterogeneous in their taste for product characteristics, price sensitivity and willingness to travel. To model this, I define consumer-specific random coefficients $\alpha_i = (\alpha_i^x, \alpha_i^p, \alpha_i^d)$ for car characteristics, price, and distance to the dealer, respectively. Following the literature, I assume that consumers are completely informed about all time t related information when making decisions at time t. Moreover, consumers have idiosyncratic shocks to their preferences for each product and in each period ε_{ijt}, which I assume as being i.i.d. across (i, j, t).[7]

Following the random coefficients discrete choice framework of Berry et al. (1995), consumer i obtains the following one-period utilities for each available choice at time period t:

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[6] λ is currently assumed to be the same across all cars. However, this can be relaxed to allow brand-varying depreciation rates.

[7] Logit errors (and most i.i.d error terms) typically imply unrealistic welfare gains from new products (see Petrin 2002). Ackerberg and Rysman (2005) argue that this feature of the logit-based demand model make them inappropriate in contexts where consumers face a vastly different numbers of products over time. Ackerberg and Rysman recommend addressing this problem by including the log of the number of products, $ln(J_t)$, as a regressor. A coefficient of 0 on the associated parameter implies the logit model is well specified, whereas a coefficient of -1 implies “full crowding," so there is no demand expansion effect from increasing variety of new products.

$$u_{ijt} = \alpha_c^e C_{jt} + \alpha_g^e G_{jt} - \alpha_i^d d_{ij} + \alpha_i^x x_{jt} + \xi_{jt} - \alpha_i^p p_{jt} + \varepsilon_{ijt},\ j = 1,...,J_t$$

where C_{jt} (G_{jt}) is an indicator variable that is equal to 1 if the product j is a Chrysler LLC (GM) brand and time period t is after Chrysler LLC (GM)'s bankruptcy. Since I include the manufacturer dummies in x_{jt}, the parameters α_c^e and α_g^e capture the incremental impact of Chapter 11 bankruptcy on the brand equity of Chrysler LLC and GM, respectively.[8]

Also I define the gross flow utility from product j purchased at time period t as $\delta_{ijt}^f = \alpha_c^e C_{jt} + \alpha_g^e G_{jt} - \alpha_i^d d_{ij} + \alpha_i^x x_{jt} + \xi_{jt}$, and the population mean flow utility as $\bar{\delta}^f{}_{jt} = \alpha_c^e C_{jt} + \alpha_g^e G_{jt} - \alpha^d d_{ij} + \alpha^x x_{jt} + \xi_{jt}$. A consumer who does not purchase a new product or does not replace her currently held car, gets a net flow utility $u_{i0t} = \delta_{i0t}^f + \varepsilon_{i0t}$. If the consumer has not purchased a product yet, the mean utility is normalized to zero, i.e. $\delta_{i0t}^f = 0$. Otherwise, it is the flow utility of the current endowment. If an automobile manufacturer terminates some of her new car dealers as part of the Chapter 11 bankruptcy reorganization, then it will impact the set of products the consumer will have access to, i.e. J_t, in each time period post bankruptcy. Disutility from travel will impact the per-period flow utility as consumers will still need to travel to dealerships to take avail of after sales services like service checkups, parts replacements, product upgrades, etc. Depending on the locations of the consumer and terminated dealerships, in the post bankruptcy period, some consumers may need to travel greater distances to purchase their most preferred car, reflected by changes in d_{ij}.

Given this model setup, in each period, each consumer makes her optimal decision as a function of her initial endowment (δ_{i0t}^f), available choices (J_t), preferences (α_i and ε_{ijt}), prices, current product attributes, and expectations over future product attributes. Let I_t denote current product characteristics and any other factors that affect product attributes in subsequent periods. I assume that I_{t+1} follows a first-order Markov process $P(I_{t+1}|I_t)$ that accounts for firm optimization behavior. Therefore, the state vector for consumer i's dynamic problem includes $(\delta_{i0t}^f, \varepsilon_{i0t}, ..., \varepsilon_{iJ_tt}, I_t)$. Then the solution to the consumer's problem is the unique solution to the following Bellman equation:

[8] Currently α_c^e and α_g^e are assumed to be the same across the entire product portfolio of the distressed manufacturer, and across all consumers. This assumption can be relaxed but comes with significant computation overhead.

$$V_i(\delta^f_{i0t}, \varepsilon_{i0t}, ..., \varepsilon_{iJ_tt}, I_t) = max\{u_{i0t} + \beta E[EV_i(\{1-\lambda\}\delta^f_{i0t}, I_{t+1})|I_t],$$
$$\max_{j=1,...,J_t}\{u_{ijt} + \beta E[EV_i(\{1-\lambda\}\delta^f_{ijt}, I_{t+1})|I_t]\}\} \tag{3.1}$$

where E denotes the expectation operator. The state space in its current form is general but too large for having a computational solution to the consumer's dynamic optimization problem. Therefore, following the literature on aggregate dynamic consumer choice models, I make the following simplifications and assumptions to reduce the dimensionality of the state space and make the aggregation across idiosyncratic preferences easier.[9]

3.5.2 Assumptions

Regarding the evaluation of consumer i's choice at time t, I make the following assumptions. Consumers have no information about the future values of the idiosyncratic shocks to their preferences for each good beyond the distribution of these shocks. These idiosyncratic shocks (ε_{ijt}) are assumed to be Type I extreme value distributed. This assumption allows me to use the aggregation properties of Type I extreme value distribution in order to rewrite equation 1 in a simpler form (Rust 1987; Anderson et al. 1992). In order to do so, let

$$\delta_{ijt} = \delta_{ij}(I_t) = \delta^f_{ijt} - \alpha^p_i p_{jt} + \beta E[EV_i(\{1-\lambda\}\delta^f_{ijt}, I_{t+1})|I_t], j = 1, ..., J_t \tag{3.2}$$

denote the mean expected discounted utility for consumer i purchasing product j at time period t. Then the *logit inclusive value*, i.e. the maximum expected utility from purchasing one of the J_t products present in the market, for consumer i at time period t, is:

$$\delta_{it} = \delta_i(I_t) = ln(\sum_{j=1,...,J_t} exp\{\delta_{ijt}\}). \tag{3.3}$$

[9]Data limitations do not permit recovery of transaction costs and revenues from trade-ins. However, if such data are available as is the case in Schiraldi (2011), extending the Bellman equation 1 to include these terms is relatively straightforward.

Under these conditions, Rust (1987) shows that the value of the optimal choice from several alternatives can be expressed as the logarithm of the sum of exponents of the mean utility of each alternative plus a single Type I extreme value draw. He also shows that a consumer's dynamic choice problem has the same expected value as a problem in which the consumer makes a one-time choice between a product with mean utility δ_{it} and the outside option with mean utility δ^f_{i0t}. Thus one can write:

$$EV_i(\delta^f_{i0t}, I_t) = \int \dots \int V_i(\delta^f_{i0t}, \varepsilon_t, I_t)p(\varepsilon_t)$$

$$= ln\left[exp(\delta_{it}) + exp\left(\delta^f_{i0t} + \beta E\left[EV_i(\{1-\lambda\}\,\delta^f_{i0t}, I_{t+1})|I_t\right]\right)\right] + \gamma$$

where $\varepsilon_t = (\varepsilon_{i0t}, \dots, \varepsilon_{iJ_t t})$, the first equality follows from the conditional independence assumption as in Rust (1987) and the second equality follows from the above discussion. Moreover, Gowrisankaran and Rysman (2009) shows that the state variable I_t has an impact on the expectation of the value function only via its effect on the current and future values of δ_{it} (i.e. $EV_i(\delta^f_{i0t}, I_t) = EV_i(\delta^f_{i0t}, \delta_{it}, P[\delta_{it+1}|I_t])$). Since the current specification is still computationally infeasible, I have to make some simplifying assumptions on the evolution of the logit inclusive value δ_{it}.

Similar to Gowrisankaran and Rysman (2009) and Schiraldi (2011), I make the *Inclusive Value Sufficiency* assumption implying that it is sufficient to condition the expectation of the value function on δ^f_{i0t} and δ_{it} rather than δ^f_{i0t} and I_t. In other words, consumers are boundedly rational, and they only use a subset of the available information when forming expectations about the future states.[10] As a result of this assumption, I can rewrite the expectation of the value function with only two state variables as follows:

$$EV_i(\delta^f_{i0t}, \delta_{it}) = ln\left[exp(\delta_{it}) + exp\left(\delta^f_{i0t} + \beta E\left[EV_i(\{1-\lambda\}\,\delta^f_{i0t}, \delta_{it+1})|\delta_{it}\right]\right)\right] + \gamma. \quad (3.4)$$

[10]Gordon (2009)instead allows consumers to form expectations on improvements at the attribute level for each current and future product. Since the set of alternatives in the automobile market is several times greater than microprocessor chips (the product market of Gordon 2009) make this approach infeasible in my empirical setting.

Then for estimation purposes, I make assumptions on the evolution of the logit inclusive value. So I assume that consumers' belief structure on the evolution of δ_{it} takes the form of the following Markov process similar to previous studies (e.g. Melnikov 2001):

$$\delta_{it+1} = \rho_{1i} + \rho_{2i}\delta_{it} + \eta_{it}, \tag{3.5}$$

where $\eta_{it} \sim N(0, \sigma_\eta)$ error term, ρ_{1i} and ρ_{2i} are consumer-specific evolution parameters to be estimated.[11]

Finally, to estimate the demand model, I make the following supply-side assumptions. Firms have rational expectations regarding future values of the product characteristics. They simultaneously make pricing decisions upon the observation of consumer holdings and current product characteristics (both observable and unobservable). In addition, product characteristics evolve exogenously. These assumptions are consistent with previous studies estimating consumer demand for durable goods (see Gowrisankaran and Rysman 2009).

3.5.3 Estimation

Identification and Instruments

Mean parameters of the utility function are identified following conventional arguments (e.g. Berry et al. 1995). In the current setting, market shares of items change as a result of differences in product characteristics and the set of available products. Note that the set of available products could change as result of product line consolidations by the manufacturer post bankruptcy, naturally evolving new product introduction and dealer network pruning. In an extreme case some brands of the distressed firm may no longer be available to consumers in a market which experiences dealer network pruning relative to another market which does not see any dealer network pruning. In our setting these factors coupled with reduction in the choice set of dealers

[11] This assumption departs from Gordon (2009) who formally models the product-specific price and quality evolution as a first-order vector autoregressive system and jointly estimates the consumer demand and supply side models.

help identify α.

The parameters of the consumer heterogeneity are identified by the set of products from which there is spillover demand due to substitution. Higher demand due to substitution from products with similar product characteristics implies larger taste heterogeneity. On the other hand, if a product draws proportionally from all products, then one concludes that consumers have very homogenous tastes. Furthermore, in contrast to static models of demand (e.g. Berry et al. 1995), my model uses inter-temporal substitution patterns as an additional source of identification for the parameters of consumer heterogeneity. For instance, if a price reduction for a product results in lower market shares for similar products in the subsequent period, the heterogeneity parameter will be identified as being large.

Following previous studies in demand estimation, I assume that the observed product characteristics are determined as part of a technological innovation process, which is exogenous to the evolution of unobserved product characteristics. Since price is possibly chosen by the firms after observing the unobserved (to the econometrician) product characteristics, price can be potentially endogenous. Previous studies such as Berry et al. (1995) and Gowrisankaran and Rysman (2009) use variables that affect the price-cost margin, including all of the product characteristics, the mean product characteristics for a given firm, the mean product characteristics for all firms, and the count of products offered by all firms, as plausible instruments for current period prices.

Similar to Nevo (2001), I conducted the Sargan-Hansen test of overidentifying restrictions to assess the quality of similar instruments. However, the test was strongly rejected. Therefore, I use an alternative set of instruments, including all of the product characteristics as well as monthly average prices in other geographically distant markets that have similar demographics (see Nevo 2001). The idea is that the prices of a product in different markets are correlated due to the common marginal cost.[12] But market specific valuations are independent across markets controlling for product characteristics and demographics. So, one could use prices in other geographic markets as instruments. A similar check of the validity of this alternative set of

[12]This assumption implies that the demand shocks across geographic markets are uncorrelated. Failure to qualify other plausible instruments using variables contained in my data limits me to this instrumenting approach.

instruments results in a failure to reject the Sargan-Hansen test of overidentifying restrictions at the 5 percent significance level. Also the first-stage F-statistic is equal to 31.56, indicating that the instruments are relevant.

Implementation

Before taking the model to the data, I need to first specify the set of observed characteristics x_{jt} to be used in the estimation. In x_{jt}, I include the dummies for the bankrupt manufacturers (i.e. Chrysler LLC and GM). I also include dealer fixed effects to control for potential endogeneity in choice of the dealerships terminated as part of the distressed firm's bankruptcy proceedings. Lastly, in order to account for product quality the following car characteristics are included: size, horsepower, reliability, miles per dollar and hybrid dummy. The distances of consumer types to dealers (d_{ij}) are included as the driving distance between the centroid of the zip code where the consumer lives and the location of the dealer. In order to capture a potential brand equity change due to Chapter 11 bankruptcy, I include the interactions of manufacturer dummies with bankruptcy dummies (C_{jt} and G_{jt}). For example, if the coefficient for the interaction between the manufacturer and bankruptcy dummies (i.e. α_c^e or α_g^e) is negative and significant, it means that consumers attach additional disutility to the products of manufacturers that have gone through Chapter 11 bankruptcy.

Given the model setup, assumptions and the specification of the observed characteristics, I also need to estimate the discount factor (β), the mean consumer sensitivity for price and consumer taste parameters [i.e. $\alpha = (\alpha_c^e, \alpha_g^e, \alpha^d, \alpha^x, \alpha^p)$] and the variance of consumer taste parameters (Σ). Following the literature on dynamic decision models, instead of estimating the discount factor, I set $\beta = 0.99$ and $\lambda = 1.25$ percent[13] at the level of month and the total market size equal to the 2008 population in the Las Vegas market.

I assume that α_i^x is constant over time and distributed normally with mean α^x and variance matrix Σ. In addition, I assume that the price sensitivity is inversely proportional to income (see Berry et al. 1999), and distribution sensitivity is inversely proportional to the distance of the individual to the market centroid. This is a novel and much simpler way to account for

[13] Industry reports and magazines generally report an average annual depreciation rate of 15 percent (e.g. www.buyingadvice.com). To reflect a similar amount, I choose a monthly rate of 1.25 percent.

consumer heterogeneity without increasing the number of parameters to be estimated. Specifically, first I draw the zip code of each consumer type using online search shares of zip codes as the probability of being chosen. Then, given the zip code draw, I use the median income for that zip code (i.e. y_i) to scale the price coefficient. That is, the price sensitivity coefficient is $\alpha_i^p = \frac{\alpha^p}{y_i}$, where α^p is a parameter to be estimated (see Schiraldi 2011). Similarly, I calculate the distance from the market centroid for the given zip code draw (i.e. τ_i) to scale the distance coefficient. So the distance sensitivity coefficient is $\alpha_i^d = \frac{\alpha^d}{\tau_i}$, where α^d is a parameter to be estimated. As in Schiraldi (2011), using exogenous income and centroid distance information increases the efficiency of the estimation procedure.

When it comes to the estimation of taste parameters and their variances, I use the framework developed by Gowrisankaran and Rysman (2009). In essence, this method combines the approaches of Berry et al. (1995) and Rust (1987). Thus it can be decomposed into three levels of nonlinear optimizations as explained below. The first step before the three levels of optimizations includes the initialization of parameters and preparation of data. The details of this step are as follows:

First, I initialize the following parameters: the number of sample individuals, the number of bins for discretizing the flow utility from the product currently owned (i.e. 20 evenly spaced grid points), upper and lower bounds for discretizing the flow utility from the product currently owned (i.e. 20 percent above and below observed values), the number of bins for logit inclusive value discretization (i.e. 50 evenly spaced grid points), upper and lower bounds for logit inclusive value discretization (i.e. 20 percent above and below observed values), discount rate (i.e.. β = 0.99), dampening parameter (i.e.. $\varphi = 1 - \beta$), and market size. Second, I determine starting values for the nonlinear parameters. Third, I initialize each consumer type, which is characterized by a value function and a transition matrix. Finally, I calculate the first-stage weight matrix, $W = (z'z)^{-1}$, using the vector of instruments for the first stage of nonlinear search.

Figure 7, illustrates the various building blocks and the sequence of procedures that govern my inference procedure. These can be broadly classified as a three level optimization procedure.

Level 1 (inner loop) consists of calculating the vector of predicted market shares as a function of the vector of population mean utilities and necessary parameters by solving the consumer dynamic programming problem for the predetermined number of simulated consumer types and then integrating across consumer types. The details are as follows:

Step 1: For each consumer type draw, start with some initial guesses identified in the initial step and compute the logit inclusive values using equation 3.

Step 2: Use the logit inclusive values to calculate the coefficients of the product evolution Markov process regression (ρ_1 and ρ_2) in equation 5.

Step 3: Use these logit inclusive values and the transition matrix found by using product evolution coefficients to calculate the expectation from equation 4. Repeat this process until convergence.

Step 4: Using the probability that consumer i buys product j ($\hat{s}_{ij}$) and calculated values of δ_{ijt} and δ_{it}, solve for market share for the current draw by starting at time 0 with the assumption that all consumers hold the outside good. Note that the probability that consumer i buys product j can be written as the aggregate probability of purchase times the probability of buying a specific product conditional on purchase as follows:

$$\begin{aligned}\hat{s}_{ij}(\delta^f_{i0t}, \delta_{ijt}, \delta_{it}) &= \frac{exp(\delta_{it})}{exp[EV_i(\delta^f_{i0t}, \delta_{it}) - \gamma]} \times \frac{exp(\delta_{ijt})}{exp(\delta_{it})} \\ &= exp[\delta_{ijt} - EV_i(\delta^f_{i0t}, \delta_{it}) + \gamma]. \end{aligned} \tag{3.6}$$

Iteratively for subsequent time periods, solve for consumer purchase decisions given the distribution of flow utility of holdings using equation 6, and update the distribution of flow utility of holdings based on purchases.

Step 5: Finally, aggregate across draws using importance sampling and calculate model predicted market shares $\hat{s}_{jt}$.

Level 2 (middle loop) includes running a fixed-point calculation of the vector of population mean flow utilities. To do this, I iterate the following fixed-point equation using the model predicted market shares computed in Level 1 ($\hat{s}_{jt}$), actual market shares (s_{jt}), and the predetermined tuning parameter (φ).

$$\bar{\delta}_{jt}^{f,new} = \bar{\delta}_{jt}^{f,old} + \varphi[ln(s_{jt}) - ln(\hat{s}_{jt})]. \tag{3.7}$$

Then I continue until full convergence of equation 7 (along with equations 3, 4, and 5).

Level 3 (outer loop) consists of running a simplex search over the nonlinear parameters. To be more precise, I minimize the following equation:

$$(\hat{\alpha}, \hat{\Sigma}) = argmin_{\alpha,\Sigma}\{G(\alpha,\Sigma)'WG(\alpha,\Sigma)\}, \tag{3.8}$$

where $G(\alpha,\Sigma)$ is a vector of stacked moments and W is a weighting matrix, by performing a two-stage nonlinear search over the nonlinear parameters using a simplex method to obtain asymptotically efficient estimates. In the first stage, I let the initial weighting matrix $W = (z'z)^{-1}$. For each candidate of nonlinear parameter vector, first I obtain $\bar{\delta}_{jt}^{f}$ vector from Level 2. Then I solve, in closed form, for the α^x that minimizes equation 8 given the $\bar{\delta}_{jt}^{f}$ vector. Next I use the first-stage estimates to approximate the optimal weighting matrix. Finally, using this approximation and other necessary parameters, I obtain the second-stage estimates for all parameters (i.e. linear as well as nonlinear).

3.6 Results

I present the parameter estimates of the calibrated model in Table 17.[14] The full model specification involves a deterministic product depreciation component as well as heterogeneity in the constant term, price sensitivity and distance sensitivity. In addition, the estimation of the full model is based on the seasonally adjusted data.[15] Most of the coefficients have expected signs, and they are precisely estimated.

A person with mean tastes would obtain a negative gross flow utility from an alternative with

[14] I estimated several models. Each with slightly different set of demand drivers, with and without product depreciation, with and without dealer fixed effects, etc. I also estimated these with models with different number of consumer types. Given space constraints, I am only reporting the results of the final model.

[15] To seasonally adjust the data, I multiply sales by a separate constant for each month that is constant across years following Gowrisankaran and Rysman (2009).

all its characteristics zero (relative to the outside option), with a mean constant term of -5.20. The standard deviation on the constant term in the consumer population is 1.59, indicating that there is substantial variation in the gross flow utility from a new car. All of the estimated parameters on the automobile characteristics are comparable in absolute value to the parameter on the constant term (-12.17 for price and -3.90 for distance to the dealer). This imply that not only are these inside good features important drivers of consumer choice, but that the vertical differentiation between our inside good automobiles is comparable to the differentiation from the outside good (Gowrisankaran and Rysman 2009).

Utility decreases with price and physical distance to the dealer. Size, horsepower and reliability increase utility, whereas miles per dollar reduces it, which is in line with what previous studies report (Berry et al. 1995; Petrin 2002). The dummy for hybrid cars indicate that people prefer a traditional car over a hybrid car.[16]

As for the bankruptcy-induced brand equity change coefficients, Table 17 suggests that brand equities of the two bankrupt manufacturers significantly changed after their bankruptcies. Interestingly, whereas the brand equity of Chrysler LLC decreased (-0.68) after it filed for Chapter 11 bankruptcy protection, that of GM increased (0.56) after GM filed for Chapter 11 bankruptcy. This result is important in that it shows the direction of the impact of Chapter 11 bankruptcy on brand equity varies by bankrupt firm.

In order to check the face validity of my model, I calculate the price elasticities across different car models. The price elasticities are generated as follows. First, I use the observed data to solve the consumer problem and estimate a baseline level of demand. Second, I generate the new price data series by increasing the price of a focal car model by 10 percent. I then re-solve the dynamic optimization problem for consumers while allowing them to update their beliefs. Finally, I compare these new market shares to the baseline market shares to compute price elasticities. I report the summary statistics across various car segments in Table 18. The recovered price elasticities range between -4.15 and -2.24, which are in line with the price elasticities

[16]First, hybrid cars account for a very small share of the overall market. Second, the hybrid dummy captures consumers innate preference for hybrid cars after controlling for fuel efficiency gains. The negative sign suggests that aspects including design may have led to a negative perception toward hybrids for an average consumer. This finding is in line with industry analyst reports.

found in previous studies estimating demand for new cars (e.g. Schiraldi 2011).

3.7 Counterfactual Simulations

The results from the previous section suggest that consumers' when, what and where-to-buy decisions are impacted by Chapter 11 bankruptcy filing decisions of automobile manufacturers. Emergence from Chapter 11 bankruptcy helps increase GM's brand equity while the brand equity of Chrysler LLC drops after emerging from bankruptcy protection. In addition, the results indicate that consumers' utility significantly decreases with physical distance to the dealer. This implies that in a market with spatially differentiated dealers and spatially dispersed consumers, bankruptcy induced distribution network pruning will also directly impact consumers' where-to-buy decisions.

In this section, I quantify the differential impact of bankruptcy-induced brand equity changes and bankruptcy-induced distribution network pruning on what, when, and where consumers buy. To do so, I compute brand and retailer-level market shares and sales across several counterfactual scenarios and compare them with baseline market shares. Baseline scenario involves choices predicted using the proposed model and the observed data.

3.7.1 Impact of Brand Equity Change on What- and When-to-Buy Decisions

To quantify the impact of brand equity change on consumers' what and when-to-buy decisions, I run two counterfactual simulations. In counterfactual scenario 1, I assess the impact of Chrysler LLC's brand equity decrease. Specifically, I simulate market shares for the market where GM's brand equity increases and Chrysler LLC closes dealerships but where Chrysler LLC's brand equity remains the same. Then I compare these market shares with the baseline market shares. Similarly, in counterfactual scenario 2, I evaluate the effect of GM's brand equity increase on consumer's brand and inter-temporal demand substitution. In order to do so, I simulate market shares in the situation where Chrysler LLC's brand equity decreases and its dealers are closed, but GM's brand equity remains the same. Again, I compare the market shares computed under this scenario with the baseline market shares to quantify the extent and timing of consumer switching.

Figure 8 shows the impact of Chrysler LLC's Chapter 11 bankruptcy filing on consumers' what-to-buy decisions. The results suggest that approximately 8 percent of Chrysler LLC consumers switch to other brands or defer their purchase (2.63 percent) due to the reduction in Chrysler LLC's brand equity. The Chrysler brand of Chrysler LLC is the most negatively affected brand due to reduction in Chrysler LLC's brand equity. On the other hand, Chrysler LLC's Dodge brand's market share is not affected very much by the erosion in Chrysler LLC's brand equity. When Chrysler LLC files for Chapter 11 protection, most of Chrysler LLC's prospective customers who switch, switch to Japanese brands such as Toyota (1.35 percent) and Honda (1.32 percent) as opposed to the incumbent American brands such as Chevrolet (0.07 percent) and Ford (0.12 percent). The simulations suggests that the brand equity changes caused by Chrysler LLC seeking bankruptcy protection varies significantly across Chrysler LLC's brand portfolio.

Figure 9 depicts the impact of GM filing for Chapter 11 bankruptcy protection. As can be seen, Chevrolet realizes higher sales. This is because the net brand equity of GM is higher after emerging from bankruptcy than its predecessor, i.e. financially distressed GM. Not only does GM draw share away from prospective Honda buyers, but it does so by accelerating their purchase by a few months (i.e. inter-temporal demand substitution).

3.7.2 Impact of Distribution Reorganization on What- and Where-to-Buy Decisions

In order to quantify the impact of bankruptcy induced distribution reorganization on consumers' what and where-to-buy decisions, I run counterfactual scenario 3. In this scenario, I compute market shares for the market where there exist significant brand equity changes for both Chrysler LLC and GM but where no dealer closings happened. Then I compare counterfactual scenario 3 market shares with baseline market shares to assess brand and retailer substitution.

Figure 10 shows the effect of Chrysler LLC's dealer network pruning on cumulative brand level substitutions. Chrysler LLC's Dodge brand stands to lose substantially (-15.8 percent) while Chrysler LLC's Chrysler brand is not impacted as much (-1.74 percent). The results suggests heterogeneous distribution network structure effects at the brand level. When it comes to Chrysler LLC's competitors, Honda (7.9 percent) and Toyota (2.97 percent) benefit the most from Chrysler LLC's dealer network pruning, while Ford gains the least (0.13 percent).

Do all Honda dealers gain from Chrysler LLC's dealer network pruning? Do some Honda dealers gain more than others? Since my model is at the retailer level, I can directly address these questions as well. In Figure 11, I plot the locations and market share gains of two Honda and two Toyota dealers due to Chrysler LLC's dealer network pruning. The results clearly show that the substitution effects from tempered competition is quite heterogeneous across competing manufacturers' dealers and also within dealers of the same competing manufacturer. For example, whereas the Honda dealer that is closer to the terminated Chrysler LLC dealers gains 7.58 percent of the switching consumers, the more distant Honda dealer only attracts 0.25 percent of the prospective Chrysler LLC customers. The incremental gains from Chrysler LLC's dealer network pruning are quite similar across Toyota dealers (1.81 percent vs. 1.16 percent).

3.7.3 Differential Impact of Brand Equity Change and Distribution Reorganization on What-to-Buy Decisions

In the last two sections, I quantified the impact of brand equity change and distribution reorganization on consumers' what-to-buy decisions separately. In this section, I compare the results from counterfactual scenario 1 and counterfactual scenario 3 to assess the relative importance of these two drivers on the outcomes for the bankrupt firm (i.e. Chrysler LLC) as well as competitor brands.

Table 19 shows the decomposition of the impact of Chrysler LLC's Chapter 11 induced brand equity change and distribution network reorganization by various brands. Interestingly, the results reveal differential impact of Chapter 11 induced brand equity and distribution network structure changes across two key brands of the bankrupt manufacturer. Dodge is negatively affected most by distribution network pruning, whereas the Chrysler brand is hurt most by reduction in Chrysler LLC's brand equity.

When it comes to the implications for competitor brands, the results suggest that they mostly gain from Chrysler LLC's distribution network pruning. In contrast, the reduction in Chrysler LLC's brand equity leads more prospective Chrysler LLC consumers to defer their purchase than the reduction in distribution network.

3.8 Conclusion

This paper studies the effect of bankruptcy-induced brand equity changes and distribution reorganization on consumers' product adoption decisions in the market for new automobiles. The analysis is based on a dynamic structural demand model using aggregate data at the retailer product level. The model and estimation feature spatial differentiation, deterministic product depreciation and the use of consumer level online search data in addition to consumer heterogeneity, endogenous prices and repeat purchases. The estimated model is used to simulate the behavior of consumers in various counterfactual environments.

The counterfactual simulations suggest that bankruptcy-induced brand equity changes and distribution reorganization result in substantial and heterogeneous brand and retailer level substitution. I find that around 21 percent of potential Chrysler LLC consumers switch to other brands, whereas around four percent decide not to buy due to decreased brand equity and distribution intensity. In addition, bankruptcy-induced brand equity changes and distribution reorganization also impact consumers purchase timing decisions. Surprisingly, the results suggest differential effect of brand equity change and distribution reorganization on different brands of the bankrupt manufacturer as well as on different competitor brands. Dodge lose consumers mainly due to dealer closings, while Chrysler is negatively affected most by the decrease in brand equity. When it comes to the implications for competitor brands, the results suggest that they mostly gain due to dealer closings. In contrast, brand equity effect leads more consumers to defer purchase than the distribution effect.

The analysis relies on several important assumptions that are either rooted in data limitation or computational feasibility. First, the model is estimated using data from a single geographic market and two categories in order to alleviate the computational burden. A fruitful extension would be to replicate the analysis across multiple categories and geographic markets.

Second, although this study extends previous literature (Gowrisankaran and Rysman 2009) by introducing a deterministic product depreciation component, an ideal approach would be to incorporate used car prices to account for depreciation (Schiraldi 2011).

Third, similar to several previous studies, I do not observe consumers' initial product holdings. Therefore, I currently make a simplifying assumption that all consumer types enter the product market with the same product, i.e. the outside no car option.[17]

Fourth, data limitations prevent me from separately identifying used cars' trade-in sales from non trade-in sales. For this reason, transactional costs from trading the current car in the secondary market are abstracted away.

Fifth, since the estimation is based on aggregate data, consumers are assumed to be persistently heterogeneous. This assumption could be relaxed if individual-level data were available.

Despite these limitations, much ground has been covered in this study. I hope this study and findings help garner greater interest amongst marketing scholars to study the impact of Chapter 11 bankruptcy and related market exits on consumer side market outcomes.

[17] I am exploring ways to exploit the empirical distribution of used cars (arrivals and sales) contained in my database to calibrate consumers' initial automobile stock

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Table 1: Simple Matching Estimator for 8 Cities, 3 Time Periods

Obs	City	t	W	X	Y	Chrys.	Dodge	Jeep	$J_M(city,t)$	$\hat{Y}_{city,t}(0)$	$\hat{Y}_{city,t}(1)$	$Z_M(city,t)$
1	1	1	1	5	7	1	0	0	{19}	5	7	3
2	1	2	1	8	6	1	0	0	{17}	7	6	3
3	1	3	1	4	8	1	0	0	{18}	6	8	1
4	2	1	1	6	7	0	1	0	{10}	4	7	2
5	2	2	1	2	9	0	1	0	{20}	1	9	0
6	2	3	1	7	1	0	1	0	{15,21}	5.5	1	3
7	3	1	1	5	0	0	0	1	{19}	5	0	3
8	3	2	1	4	2	0	0	1	{20}	1	2	4
9	3	3	1	2	7	0	0	1	{24}	4	7	2
10	4	1	0	7	4	0	0	0	{4}	7	7	1
11	4	2	0	6	7	0	0	0	{2,8}	6	4	0
12	4	3	0	6	4	0	0	0	{6}	6	1	0
13	5	1	0	1	8	0	0	0	{1,7}	1	3.5	0
14	5	2	0	6	9	0	0	0	{2,8}	6	4	0
15	5	3	0	7	1	0	0	0	{6}	7	1	1
16	6	1	0	2	6	0	0	0	{1,7}	2	3.5	0
17	6	2	0	8	7	0	0	0	{2}	8	6	1
18	6	3	0	3	6	0	0	0	{3,9}	3	7.5	0
19	7	1	0	4	5	0	0	0	{1,7}	4	3.5	2
20	7	2	0	4	1	0	0	0	{8}	4	2	2
21	7	3	0	7	10	0	0	0	{6}	7	1	1
22	8	1	0	8	10	0	0	0	{4}	8	7	0
23	8	2	0	5	6	0	0	0	{8}	5	2	0
24	8	3	0	2	4	0	0	0	{9}	2	7	1

Table 2: Descriptive Statistics for Marketing Mix Variables and Sales

Descriptive Statistics of Treatment and Non-Treatment Observations (by Exited Brand)												
	Price			Assortment size			Inventory			Sales		
Exited Brand	Obs Treated (Non treated)	Treated Mean (St. Dev.)	Non treated Mean (St. Dev.)	Obs Treated (Non treated)	Treate d Mean (St. Dev.)	Non treate d Mean (St. Dev.)	Obs Treated (Non treated)	Treated Mean (St. Dev.)	Non treated Mean (St. Dev.)	Obs Treated (Non treated)	Treated Mean (St. Dev.)	Non treated Mean (St. Dev.)
Chrysler	194 (36,822)	30,652 (7,686)	30,268 (13,522)	300 (51,986)	2.41 (1.43)	2.23 (1.38)	300 (51,986)	10.64 (22.53)	8.91 (14.75)	240 (39,092)	10.27 (16.75)	9.35 (16.69)
Dodge	412 (36,604)	29,753 (8,167)	30,276 (13,546)	488 (51,798)	2,39 (1.57)	2.23 (1.38)	488 (51,798)	16.92 (23.02)	8.84 (14.69)	394 (38,938)	14.03 (23.24)	9.31 (16.60)
Jeep	786 (36,230)	29,248 (8,305)	30,292 (13,588)	1,028 (51,258)	2,10 (1.29)	2.24 (1.38)	1,028 (51,258)	6.10 (8.00)	8.97 (14.91)	658 (38,674)	5.52 (6.72)	9.42 (16.80)

Table 3: Number of Observations by Terminated Brand-Incumbent Category

	Treatment and Non-Treatment Observations (Exited Brand X Incumbent Product Category)											
	Price			Assortment size			Inventory			Sales		
Brands	Chrysler Treated (Control)	Dodge Treated	Jeep Treated	Chrysler Treated (Control)	Dodge Treated	Jeep Treated	Chrysler Treated (Control)	Dodge Treated	Jeep Treated	Chrysler Treated (Control)	Dodge Treated	Jeep Treated
Convertible	8 (1,787)	37	34	16 (2,651)	46	53	16 (2,651)	46	53	5 (843)	15	14
Coupe	23 (4,531)	42	98	35 (6,258)	53	120	35 (6,258)	53	120	25 (4,189)	45	57
Hatchback	16 (3,157)	45	94	28 (4,657)	51	123	28 (4,657)	51	123	20 (3,438)	41	73
Sedan	32 (6,283)	70	148	47 (8,673)	81	188	47 (8,673)	81	188	44 (7,231)	73	141
SUV	39 (6,447)	75	150	52 (8,932)	86	192	52 (8,932)	86	192	47 (7,751)	80	136
Truck	30 (5,307)	48	115	49 (7,366)	59	145	49 (7,366)	59	145	46 (6,721)	53	123
Van	30 (4,782)	58	95	47 (6,831)	68	130	47 (6,831)	68	130	31 (4,396)	56	67
Wagon	16 (2,142)	37	51	26 (3,247)	43	76	26 (3,247)	43	76	22 (2,081)	31	46

Table 4: Number of Observations by Terminated Brand-Incumbent Brand

Treatment and Non-Treatment Observations (Exited Brand X Incumbent Brand)												
	Price			Assortment size			Inventory			Sales		
Brands	**Obs for Chrysler Treated (Control)**	**Obs for Dodge Treated**	**Obs for Jeep Treated**	**Obs for Chrysler Treated (Control)**	**Obs for Dodge Treated**	**Obs for Jeep Treated**	**Obs for Chrysler Treated (Control)**	**Obs for Dodge Treated**	**Obs for Jeep Treated**	**Obs for Chrysler Treated (Control)**	**Obs for Dodge Treated**	**Obs for Jeep Treated**
Chevrolet	32 (9,377)	106	120	66 (13,083)	106	149	66 (13,083)	106	149	56 (9,338)	85	98
Ford	43 (7,207)	59	122	85 (10,147)	94	151	85 (10,147)	94	151	65 (7,805)	81	104
Chrysler	4 (2,737)	60	67	5 (3,702)	60	83	5 (3,702)	60	83	1 (2,137)	36	28
Jeep	6 (1,164)	15	21	6 (1,449)	15	29	6 (1,449)	15	29	4 (1,165)	13	10
Dodge	25 (5,602)	22	147	29 (7,309)	22	167	29 (7,309)	22	167	15 (4,399)	10	79
Mazda	0 (1,002)	24	84	0 (1,391)	29	88	0 (1,391)	29	88	0 (973)	24	58
Toyota	47 (2,877)	61	33	72 (4,875)	61	129	72 (4,875)	61	129	72 (4,938)	61	106
Nissan	37 (2,462)	65	164	37 (3,430)	70	204	37 (3,430)	70	204	27 (3,019)	56	148
Honda	0 (2,029)	61	28	0 (3,261)	31	28	0 (3,261)	31	28	0 (3,475)	28	27

Table 5: Descriptive Statistics for Observed Covariates

Variable	**Mean**	**Std. Dev.**
Gas price ($)	2.59	0.13
Employment	29,210	141,509
Number of households with no vehicle	2,567	17,697
Population	66,353	346,348
Median income ($)	68,044	21,685
Population density (per sq. mi)	1,817	2,273
Note: In the analysis, I use the logs of all the variables above.		

Table 6: Incidence and Direction of Incumbent Reactions by Category

Incidence and Direction of Incumbent Dealer Reactions and Outcomes by Car Category (Frequency of Effects)												
	Price			Assortment size			Inventory			Sales		
Categories	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -
Convertible	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Coupe	38%	13%	25%	38%	38%	38%	50%	25%	38%	25%	25%	0%
Hatchback	56%	33%	33%	44%	22%	33%	56%	22%	44%	33%	11%	22%
Sedan	100%	78%	56%	78%	56%	56%	67%	44%	56%	56%	44%	22%
Suv	90%	50%	50%	80%	60%	30%	80%	40%	50%	70%	20%	60%
Truck	71%	43%	57%	57%	43%	43%	57%	43%	43%	57%	43%	43%
Van	50%	38%	25%	0%	0%	0%	50%	25%	25%	13%	0%	13%
Wagon	43%	14%	29%	0%	0%	0%	43%	43%	14%	29%	29%	0%
Average	**64%**	**38%**	**39%**	**42%**	**31%**	**29%**	**58%**	**35%**	**39%**	**40%**	**25%**	**23%**

Note: Number of brands per category is as follows: Convertible 9; Coupe 8; Hatchback 9; Sedan 9; Suv 10; Truck 7; Van 8; Wagon 7

Table 7: Magnitude and Direction of Incumbent Reactions by Category

Magnitude of Incumbent Dealer Reactions and Outcomes by Car Category (Mean Treatment Effect)												
	Price			Assortment size			Inventory			Sales		
Categories	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -
Convertible	na	na	na	na	na	na	na	na	na	na	na	na
Coupe	-0.52%	3.01%	-11.83%	-0.19	0.81	-1.38	-0.60	6.40	-4.69	5.69	5.69	na
Hatchback	4.40%	11.16%	-17.05%	-0.54	2.07	-0.57	-3.57	14.74	-4.32	-1.88	9.07	-6.79
Sedan	4.16%	8.30%	-7.05%	0.22	0.54	-1.91	-15.50	17.74	-16.56	6.64	9.16	-11.29
Suv	4.50%	8.66%	-7.86%	0.70	0.99	-1.03	-2.18	14.85	-3.55	-4.56	9.44	-6.27
Truck	-4.42%	9.14%	-7.50%	0.17	0.77	-2.87	-8.29	21.48	-9.53	3.97	18.96	-6.87
Van	6.08%	6.80%	-8.40%	na	na	na	-1.74	1.55	-6.78	-1.91	na	-1.91
Wagon	-5.37%	4.75%	-10.53%	na	na	na	1.64	2.80	-1.78	4.90	4.90	na

Table 8: Incidence and Direction of Incumbent Reactions by Incumbent Brand

Incidence and Direction of Incumbent Dealer Reactions and Outcomes by Incumbent Brand (Frequency of Effects)												
	Price			Assortment size			Inventory			Sales		
Brands	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -
Chevrolet	63%	63%	13%	50%	50%	38%	63%	50%	50%	38%	38%	0%
Ford	63%	25%	38%	63%	50%	63%	63%	38%	38%	63%	25%	50%
Chrysler	50%	50%	17%	33%	17%	17%	33%	0%	33%	33%	33%	0%
Jeep	50%	50%	0%	50%	50%	0%	50%	50%	50%	50%	50%	50%
Dodge	63%	38%	38%	13%	13%	0%	50%	13%	38%	25%	0%	25%
Average for American cars	**58%**	**45%**	**21%**	**42%**	**36%**	**24%**	**52%**	**30%**	**42%**	**42%**	**29%**	**25%**
Mazda	43%	29%	14%	29%	0%	29%	0%	0%	0%	29%	14%	14%
Toyota	75%	63%	50%	50%	25%	50%	75%	50%	63%	63%	38%	50%
Nissan	88%	13%	88%	50%	50%	13%	63%	63%	13%	25%	0%	25%
Honda	14%	0%	14%	29%	0%	29%	57%	0%	57%	0%	0%	0%
Average for Japanese cars	**55%**	**26%**	**42%**	**40%**	**19%**	**30%**	**49%**	**28%**	**33%**	**29%**	**13%**	**22%**

Note: Number of categories by brand is as follows: Chevrolet 8; Ford 8; Chrysler 6; Jeep 2; Dodge 8; Mazda 7; Toyota 8; Nissan 8; Honda 7

Table 9: Magnitude and Direction of Incumbent Reactions by Incumbent Brand

Magnitude of Incumbent Dealer Reactions and Outcomes by Incumbent Brand (Mean Treatment Effect)												
	Price			Assortment size			Inventory			Sales		
Brands	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -
Chevrolet	5.78%	6.98%	-7.50%	0.57	0.79	-1.92	-0.65	16.05	-9.53	9.16	9.16	na
Ford	-4.16%	10.00%	-12.42%	-0.87	0.83	-4.51	12.18	25.76	-12.00	-13.41	34.28	-25.80
Chrysler	9.51%	11.96%	-18.46%	-0.04	0.35	-0.43	-2.66	na	-2.66	6.59	6.59	na
Jeep	5.56%	5.56%	na	1.44	1.44	na	16.60	38.99	-5.80	4.22	13.58	-5.14
Dodge	4.71%	26.89%	-3.16%	0.99	0.99	na	-2.54	2.47	-3.06	-4.32	na	-4.32
Average for American cars	**4%**	**12%**	**-10%**	**0.4**	**0.9**	**-2.3**	**4.6**	**20.8**	**-6.6**	**0.4**	**15.9**	**-11.8**
Mazda	4.16%	7.66%	-26.84%	-0.52	na	-0.52	na	na	na	2.97	9.91	-3.98
Toyota	3.87%	7.83%	-7.42%	-0.97	0.23	-1.33	-4.55	28.12	-10.58	-6.77	14.70	-9.55
Nissan	-15.43%	6.31%	-15.69%	0.17	0.38	-1.29	4.60	6.40	-3.54	-5.21	na	-5.21
Honda	-2.78%	na	-2.78%	-0.46	na	-0.46	-6.93	na	-6.93	na	na	na
Average for Japanese cars	**-2%**	**7%**	**-17%**	**-0.4**	**0.3**	**-0.9**	**-2.3**	**17.3**	**-7.0**	**-3.01**	**12.31**	**-6.25**

Table 10: Incidence and Direction of Incumbent Reactions by Terminated Brand

Incidence and Direction of Incumbent Dealer Reactions and Outcomes by Terminated Brand (Frequency of Effects)												
	Price			Assortment size			Inventory			Sales		
Terminated Brand	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -
Chrysler	25%	17%	8%	23%	8%	15%	23%	5%	19%	19%	2%	17%
Dodge	33%	13%	20%	22%	16%	6%	25%	19%	6%	22%	17%	5%
Jeep	30%	20%	10%	20%	14%	6%	27%	9%	17%	0%	0%	0%

Table 11: Magnitude and Direction of Incumbent Reactions by Terminated Brand

Magnitude of Incumbent Dealer Reactions and Outcomes by Terminated Brand (Mean Treatment Effect)												
	Price			Assortment size			Inventory			Sales		
Terminated Brand	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -	Significant	Sig. +	Sig. -
Chrysler	3.73%	8.25%	-7.86%	-1.29	0.81	-2.20	-6.15	10.73	-8.88	-6.87	3.53	-7.40
Dodge	-5.37%	7.76%	-11.83%	0.44	0.62	-0.50	10.39	16.27	-6.93	9.07	9.91	-2.93
Jeep	5.12%	6.80%	-6.88%	0.77	1.21	-1.47	-2.36	17.74	-4.10	na	na	na

Table 12: Incidence of Incumbent Reactions by Terminated Brand-Incumbent Brand

Incidence and Direction of Incumbent Dealer Reactions and Outcomes by Terminated Brand-Incumbent Brand (Frequency of Effects)												
	Price			**Assortment size**			**Inventory**			**Sales**		
Incumbent Brand	**Chrysler**	**Dodge**	**Jeep**	**Chrysler**	**Dodge**	**Jeep**	**Chrysler**	**Dodge**	**Jeep**	**Chrysler**	**Dodge**	**Jeep**
Chevrolet	50%	38%	63%	38%	38%	50%	25%	38%	63%	0%	38%	0%
Ford	50%	13%	38%	63%	13%	50%	63%	0%	38%	63%	0%	0%
Chrysler	NEO	33%	50%	NEO	0%	33%	NEO	0%	33%	NEO	33%	0%
Jeep	50%	0%	50%	50%	50%	50%	0%	0%	*50%*	50%	50%	0%
Dodge	38%	13%	25%	13%	0%	0%	38%	0%	*25%*	25%	NEO	NEO
Average for American cars	**47%**	**19%**	**45%**	**41%**	**20%**	**37%**	**32%**	**8%**	**42%**	**35%**	**30%**	**0%**
Mazda	NEO	43%	0%	NEO	29%	0%	NEO	0%	0%	NEO	29%	0%
Toyota	50%	50%	38%	50%	25%	13%	50%	50%	38%	50%	38%	0%
Nissan	0%	88%	13%	13%	38%	13%	13%	50%	13%	0%	25%	0%
Honda	NEO	0%	14%	NEO	29%	0%	NEO	57%	0%	NEO	0%	0%
Average for Japanese cars	**25%**	**45%**	**16%**	**32%**	**30%**	**7%**	**32%**	**39%**	**13%**	**25%**	**23%**	**0%**

Note: NEO means not enough observation to estimate an effect.

Table 13: Magnitude of Incumbent Reactions by Terminated Brand-Incumbent Brand

Magnitude of Incumbent Dealer Reactions and Outcomes by Terminated Brand-Incumbent Brand (Mean Treatment Effect)												
	Price			Assortment size			Inventory			Sales		
Incumbent Brand	**Chrysler**	**Dodge**	**Jeep**	**Chrysler**	**Dodge**	**Jeep**	**Chrysler**	**Dodge**	**Jeep**	**Chrysler**	**Dodge**	**Jeep**
Chevrolet	3.30%	7.21%	4.81%	0.58	0.79	-1.49	-9.53	16.48	-2.18	na	9.16	na
Ford	-12.95%	-4.42%	7.28%	-4.51	0.76	0.90	-9.46	na	17.74	-12.50	na	na
Chrysler	na	11.13%	9.51%	na	na	-0.04	na	na	-2.66	-9.55	6.59	na
Jeep	5.70%	na	5.42%	0.81	1.51	1.44	na	na	*-5.80*	-5.14	13.58	na
Dodge	11.06%	26.89%	-10.11%	0.99	na	na	-2.14	na	*-3.06*	-4.32	na	na
Average for American cars	**1.78%**	**10.20%**	**3.38%**	**-0.53**	**1.02**	**0.20**	**-7.04**	**16.48**	**0.81**	**-7.88**	**9.78**	**na**
Mazda	na	4.16%	na	na	-0.52	na	na	na	na	na	2.97	na
Toyota	7.49%	-6.40%	5.85%	-1.33	0.23	0.23	-9.62	13.19	-10.58	na	10.54	na
Nissan	na	-15.69%	6.31%	-1.29	0.58	0.17	-3.54	7.00	0.62	na	-5.21	na
Honda	na	na	-2.78%	na	-0.46	na	na	-6.93	na	na	na	na
Average for Japanese cars	**7.49%**	**-5.98%**	**3.13%**	**-1.31**	**-0.04**	**0.20**	**-6.58**	**4.42**	**-4.98**	**na**	**2.77**	**na**

Table 14: Literature on Bankruptcy Filings and Market Outcomes

Bankruptcy Filings and Market Outcomes			
Study	**Literature/Industry**	**Approach**	**Focus (Variables)**
Borenstein and Rose ’95 (AER)	Economics/Airline	Reduced form	Supply side (price)
Borenstein and Rose ’03 (AER)	Economics/Airline	Reduced form	Supply side (service level)
Ciliberto and Schenone ’10	Economics/Airline	Reduced form	Supply side (price, network structure, capacity)
Öztürk, Venkataraman and Chintagunta ’11	Marketing/Auto	Reduced form	Supply side (price, assortment, inventory)
This study	**Marketing/Auto**	**Structural**	**Consumer side**

Table 15: Comparison with Similar Studies That Estimate Dynamic Demand Models Using Aggregate Data

Key Structural Drivers of Consumer Adoption Decisions				
Study	**Forward-Looking Behavior**	**Spatial Differentiation**	**Heterogeneous Consumer Tastes**	**Product Depreciation**
Melnikov (2001)	Yes	No	No	No
Gowrisankaran and Rysman (2009); Gordon (2009)	Yes	No	Yes	No
Schiraldi (2011)	Yes	No	Yes	Yes
This Study	***Yes***	***Yes***	***Yes+Use of Online Search Data***	***Yes***

Table 16: Descriptive Statistics

Continuous Variables	Mean	Std. Dev.	Min	Max
Sales (units)	11.33	13.05	1	94
Price (in $1000s)	22.06	5.21	12.92	48.41
Size (sq. inch in 1000s)	12.91	1.22	10.05	14.91
Horsepower	148.92	28.15	76	190
Reliability	3.61	0.80	2	5
Miles per dollar	11.05	3.62	4.61	29.13
Latitude	36.16	0.05	36.07	36.28
Longitude	-115.20	0.06	-115.28	-115.10
Dummy Variables	**Percentage Occurrence**		**Min**	**Max**
Hybrid	11.01%		0	1
Chrysler LLC	12.1%		0	1
GM	5.0%		0	1

Table 17: Parameter Estimates

Mean coefficients (α)	Estimate	Standard Error
Constant	-5.20*	0.02
Price	-12.17*	0.03
Distance	-3.90*	0.02
Chrysler LLC	0.62*	0.01
GM	-1.63*	0.01
Chrysler LLC x Bankruptcy	-0.68*	0.01
GM x Bankruptcy	0.56*	0.01
Size	0.25*	< 0.01
Horsepower	0.003*	0.0001
Miles per dollar	-0.007*	< 0.0001
Reliability	0.009*	0.0008
Hybrid	-0.057*	< 0.01
Standard deviation coefficients ($\Sigma^{1/2}$)	**Estimate**	**Standard Error**
Constant	1.59*	< 0.01

Statistical significance at 5% level indicated with *. There are 1120 observations.
To save space, the coefficients for the dealer fixed effects are not shown.

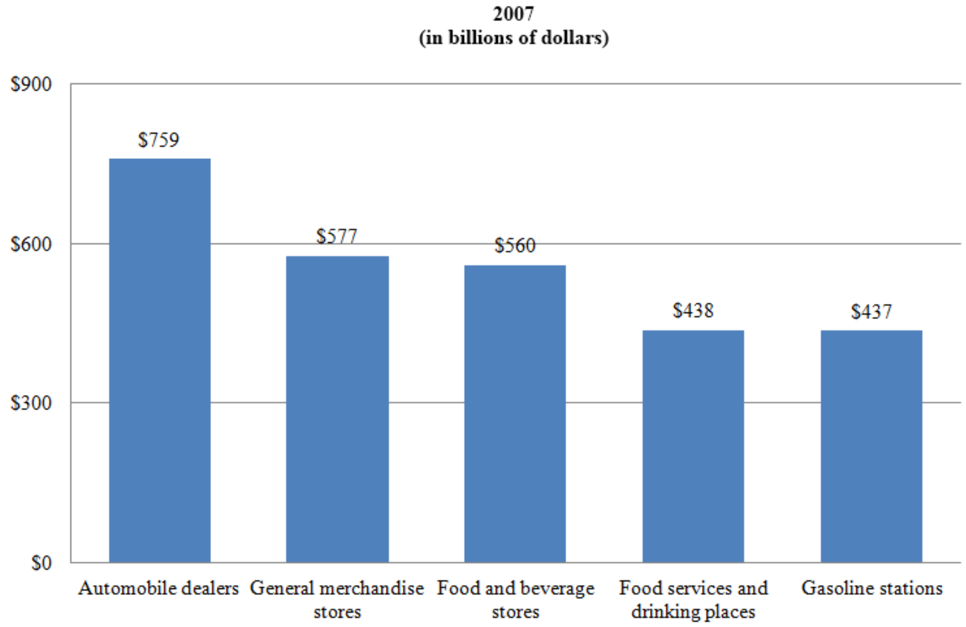
Table 18: Own Price Elasticities

Market Segment	Average	Min	Max
Small Car	-2.69	-3.10	-2.24
Midsize Car	-3.15	-4.15	-2.43
Large Car	-3.64	-3.86	-3.48

Table 19: Differential Impact of Brand Equity Change and Dealer Closings on What-to-Buy Decisions

	Brand Equity Effect (%)	***Dealer Closings Effect (%)***
Chevrolet	0.07	2.74
Chrysler	-7.96	-1.74
Dodge	-0.1	-15.80
Ford	0.12	0.13
Honda	1.32	7.90
Hyundai	1.3	0.58
Nissan	1.26	1.40
Outside	2.63	1.07
Toyota	1.35	2.97
Volkswagen	0.01	0.75

Figure 1: Contribution of Automobile Dealers to U.S. Retailing



Source: U.S. Census Bureau, Annual Retail Trade Survey, March 31, 2009, http://www.census.gov/retail/.
Notes: 2007 statistics are the most recently available data from the U.S. Census Bureau.

Figure 2: Timeline of Events Leading up to Chrysler LLC Bankruptcy and Beyond

April 2008 – With soaring gas prices, Chrysler's sales are down 23 percent.

November 18, 2008 – Chrysler's CEO appears before Congress for the first time to secure financial aid from government.

November 21, 2008 – A $25 billion plan to rescue troubled U.S. automakers collapses in Congress.

December 2, 2008 – Chrysler requests a $7 billion secured working capital bridge loan to make it through 2008 and an additional $8.5 billion load for production facility restructuring.

December 11, 2008 – The emergency loan bill for automakers fails to pass in the Senate.

December 19, 2008 – George W. Bush approves the bailout plan for Chrysler and GM, which grants a loan of $17.4 billion for the two U.S. automakers.

January 2, 2009 – Chrysler receives a $4 billion emergency loan from the federal government.

January 5, 2009 – Chrysler reports its December 2008 U.S. sales dropped 53 percent.

February 18, 2009 – Chrysler files new restructuring plans with Congress.

February 25, 2009 – Fiat, the Italian car manufacturer, says it wants to acquire a big piece of Chrysler's business.

March 30, 2009 – The White House auto task force review the merger between Chrysler and Fiat and gives Chrysler and Fiat 30 days to reach a final agreement.

April 30, 2009 – Chrysler files for bankruptcy under Chapter 11 of the bankruptcy code and Chrysler and Fiat confirm a merger between the two companies.

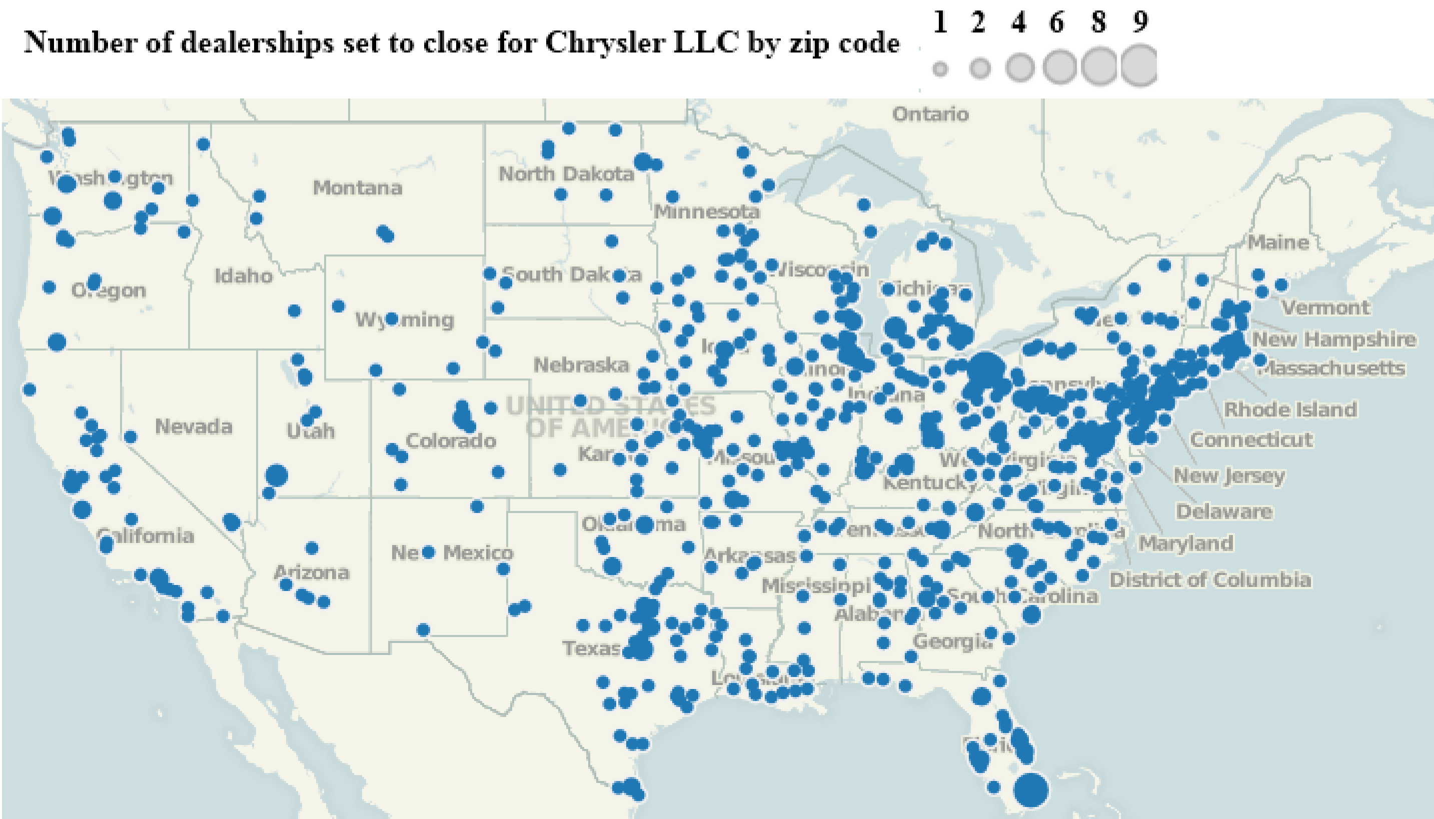
May 14, 2009 – Chrysler sends termination letter to a quarter of its U.S. dealerships as part of its restructuring efforts.

June 9, 2009 – Chrysler wins court approval to close 789 of its dealerships.

June 10, 2009 – Bankruptcy court judge approves the sale of most of Chrysler's assets to a group led by Fiat, dealership terminations are a part of sale order.

Sources: Chrysler LLC, Reuters, Public Broadcasting Service, Wikipedia.

Figure 3: Chrysler LLC Dealer Closings - Geographic Variation



Note: The list of dealerships that are set to close and their zip codes were obtained from Chrysler LLC's bankruptcy filing.

Figure 4: Las Vegas Market

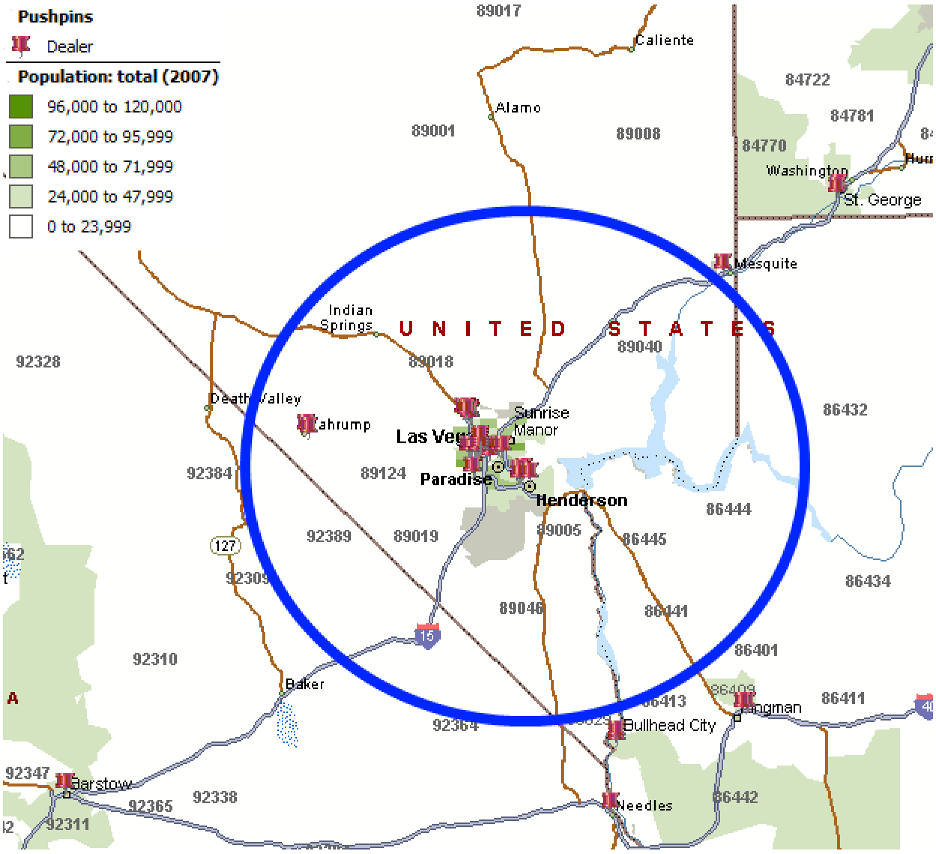
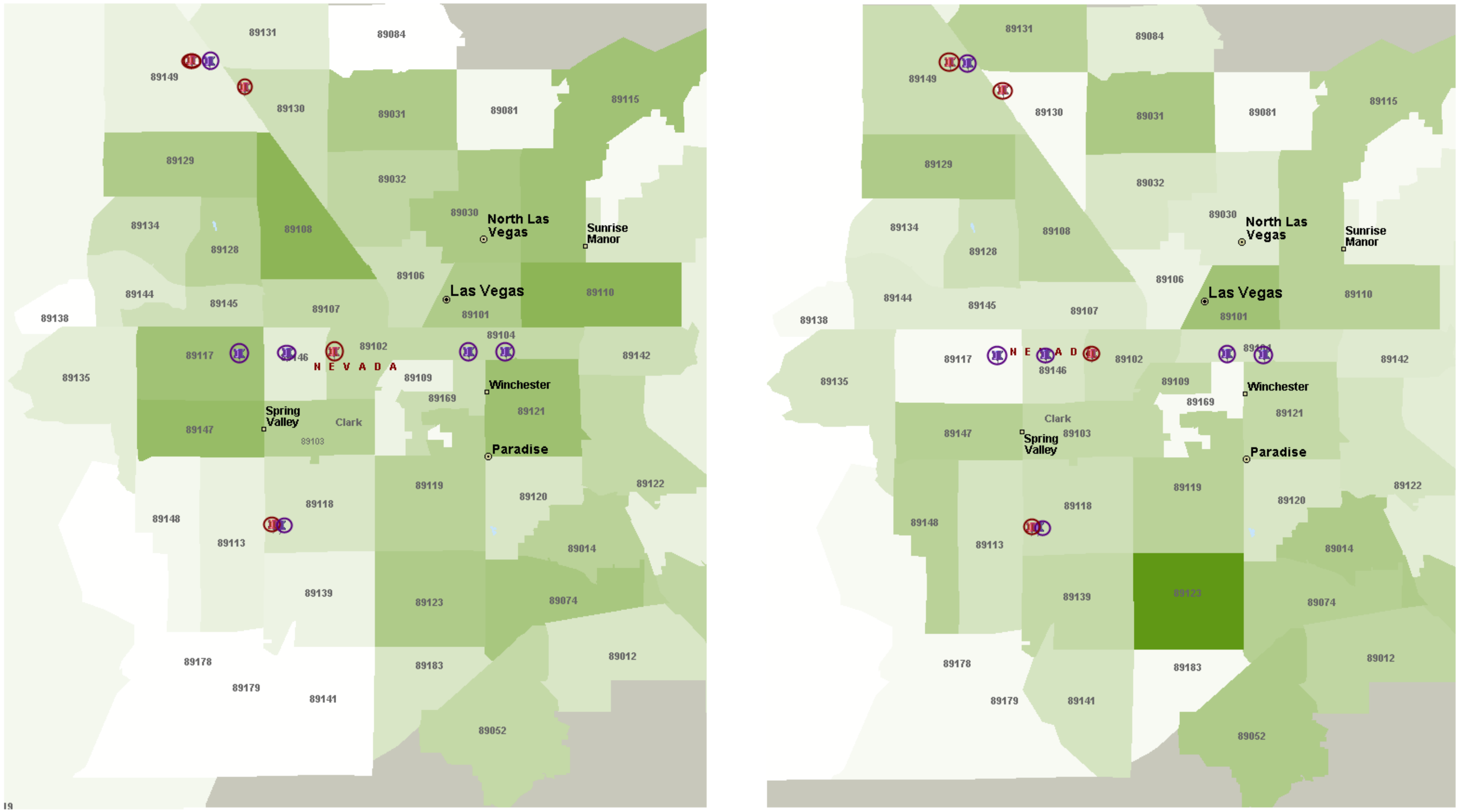


Figure 5: Population Density vs. Online Search Density by Zip Code in the Las Vegas Market

Population Density

Search Density



Note: Darker shades indicate higher population or search density zips in the market.

Figure 6: Brand and Dealer Level Market Share Changes After Bankruptcies

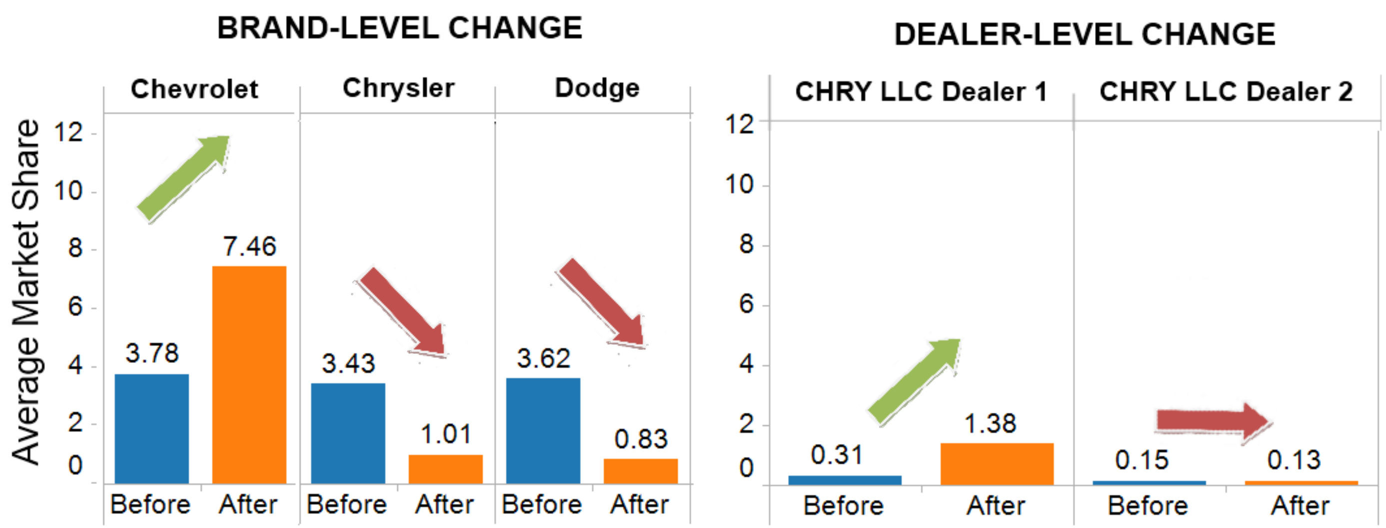


Figure 7: Estimation Overview

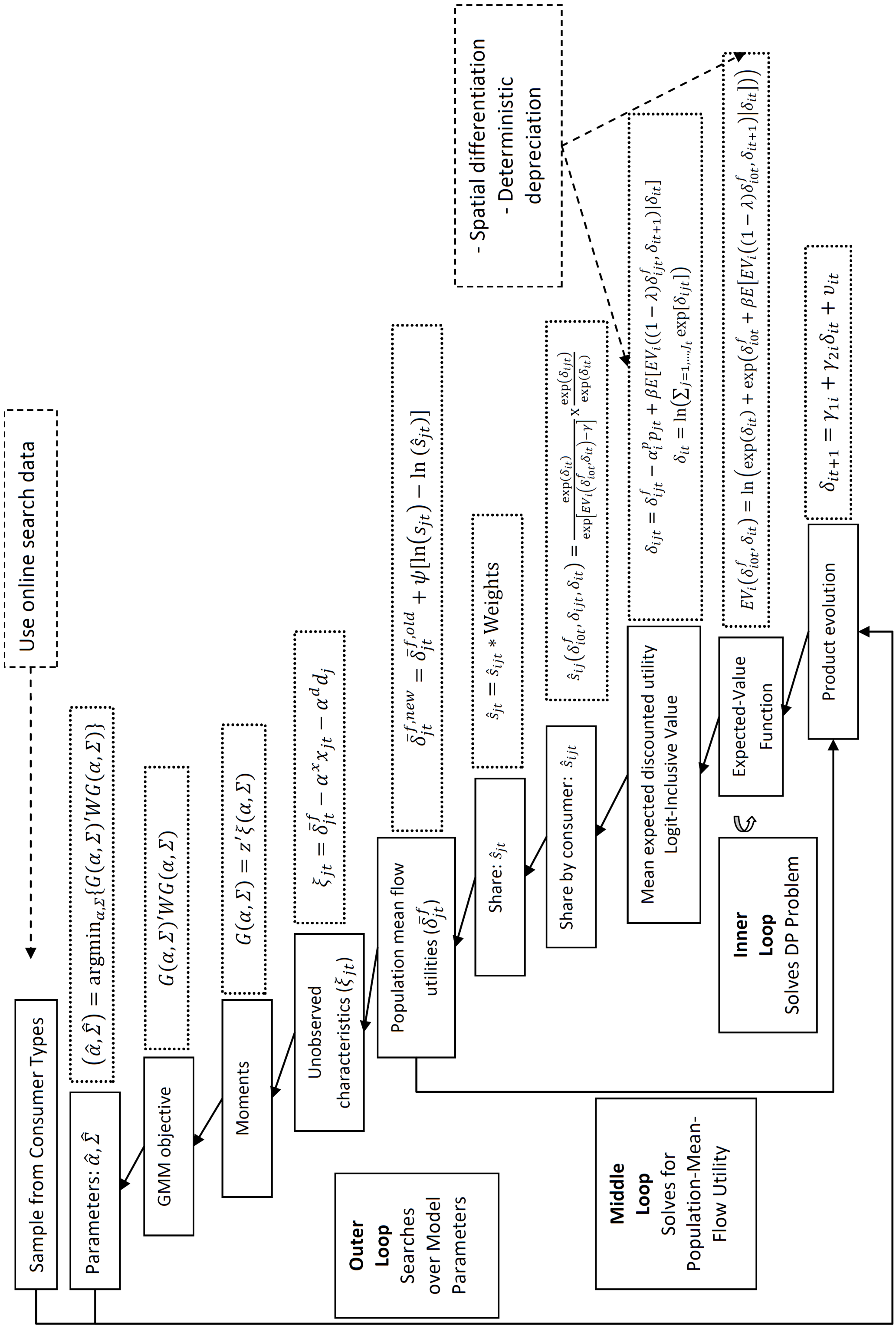


Figure 8: Impact of Brand Equity Decrease for Chrysler LLC on What-to-Buy Decisions

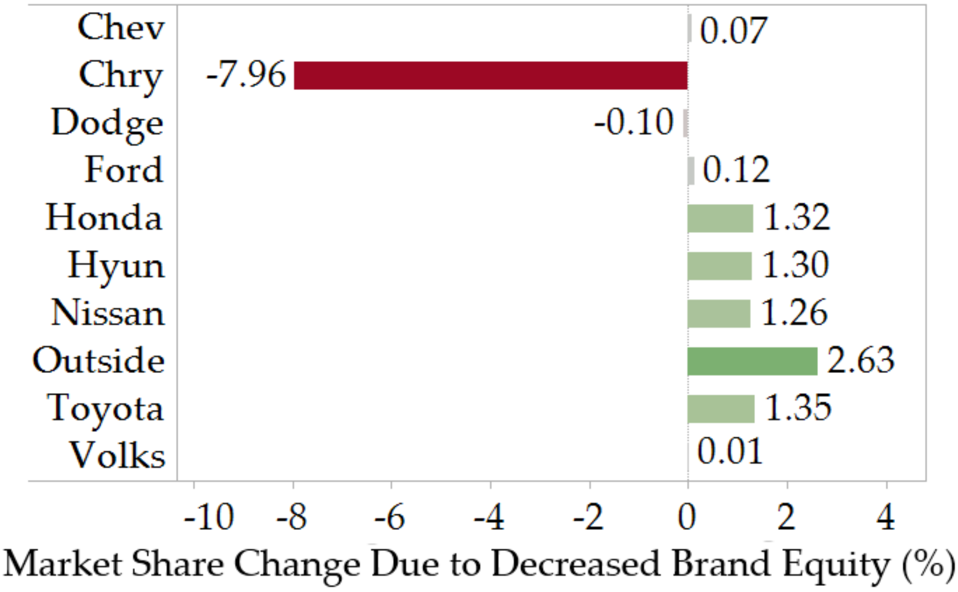


Figure 9: Impact of Brand Equity Increase for GM on When-to-Buy Decisions

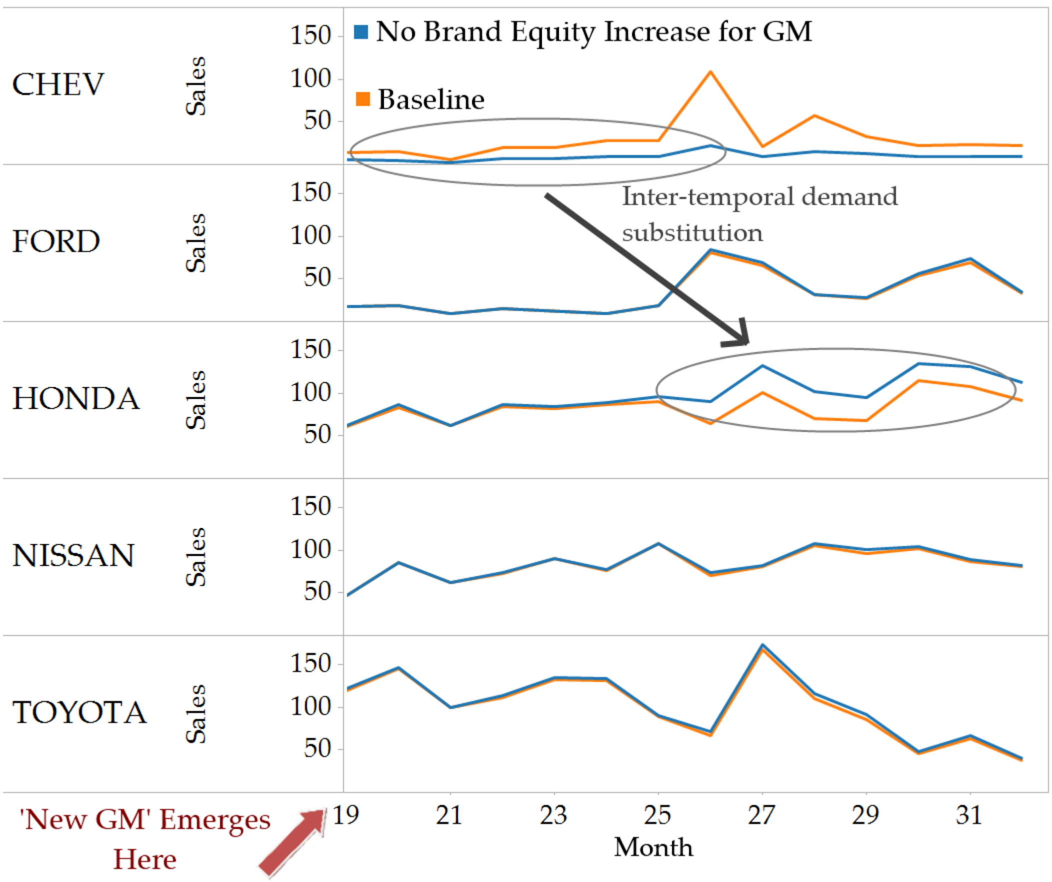


Figure 10: Impact of Distribution Reorganization on What-to-Buy Decisions

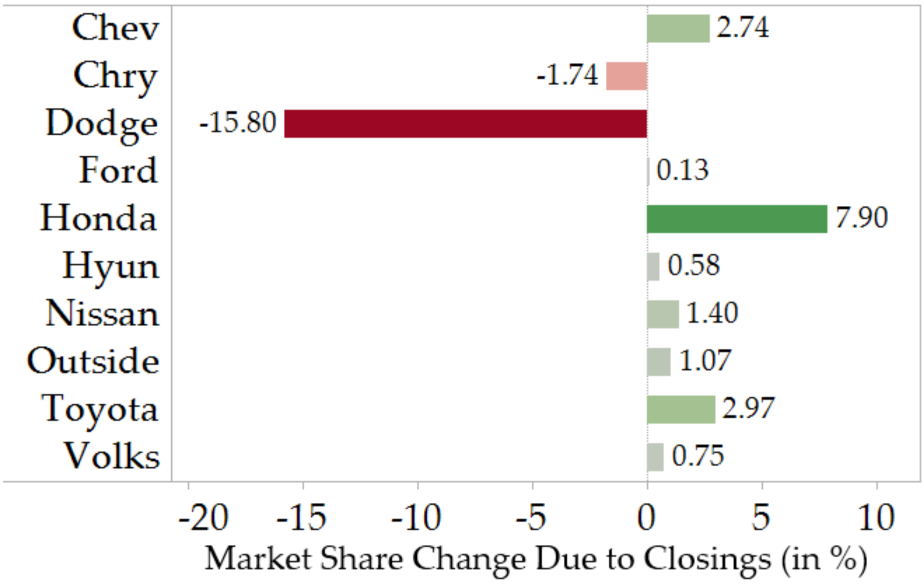


Figure 11: Impact of Distribution Reorganization on Where-to-Buy Decisions